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Robot–City Interaction: Mapping the Research Landscape—A Survey of the Interactions Between Robots and Modern Cities

Ilaria Tiddi¹ · Emanuele Bastianelli² · Enrico Daga³ · Mathieu d’Aquin⁴ · Enrico Motta³

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Abstract

The goal of this work is to describe how robots interact with complex city environments, and to identify the main characteristics of an emerging field that we call *Robot–City Interaction* (RCI). Given the central role recently gained by modern cities as use cases for the deployment of advanced technologies, and the advancements achieved in the robotics field in recent years, we assume that there is an increasing interest both in integrating robots in urban ecosystems, and in studying how they can interact and benefit from each others. Therefore, our challenge becomes to verify the emergence of such area, to assess its current state and to identify the main characteristics, core themes and research challenges associated with it. This is achieved by reviewing a preliminary body of work contributing to this area, which we classify and analyze according to an analytical framework including a set of key dimensions for the area of RCI. Such review not only serves as a preliminary state-of-the-art in the area, but also allows us to identify the main characteristics of RCI and its research landscape.

Keywords Robots · City ecosystems · Robot–City interaction · Smart cities

1 Introduction

Modern cities have become a key element of the strategies for future investments not only for the important role they play in the socio-economic growth worldwide, but also for

the increasing difficulty in being environmentally sustainable [31,71]. As a consequence, a considerable number of efforts have been put by both the academic and industrial research communities into exploiting techniques from a wide range of domains such as ubiquitous computing, data analysis and knowledge engineering, with the aim of enabling cities to be more efficient, productive and competitive [4,9,24,52,54].

Robotics has also reached increased maturity in the last decades, as demonstrated by the amount of efficient open source hardware and software components, the availability of reliable techniques for basic perception, manipulation and navigation tasks, as well as the increasing number of cost-accessible robotic platforms [82]. Thanks to these advancements, robots and autonomous systems have been identified as one of the most important modern *disruptive* technologies [66], i.e. technologies enabling massive economic transformations in the near future, and policy makers worldwide are nowadays investing to support the development of urban infrastructures able to integrate robotic technologies, therefore allowing such transformations [97].

As a consequence, national and local governments have started experimenting the integration of robots in urban spaces in the last years, with the goal of showing how such urban transformations facilitate the citizens’ everyday life and demonstrate good city governance. If we take the exam-

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(a) Starship robots delivering groceries in the centre of Milton Keynes. **(b)** Drones services for the Flying High Challenge.

Fig. 1 Civic and commercial uses of robots in UK cities

ple of the UK, several initiatives have been launched to support cities willing to develop robot and infrastructures to transform their services, e.g. the Starship delivery services¹ or the Nesta Flying Challenge² (cfr. Fig. 1). Other examples include cities deploying autonomous cars to enhance urban mobility,³ drone deliveries employed for commercial or first-aid emergency scenarios,⁴ and social robots operating in public and commercial spaces in many guises (waiters, policemen, receptionists⁵).

Considering this, the main hypothesis of our work is that the study of how robots can integrate and co-operate with city environments is emerging as a **new area of research, which we call Robot–City Interaction (RCI)**. Our challenge therefore becomes to assess the current state of this area, and to identify the main characteristics, the core themes and the research challenges associated with it. The methodology we use to achieve this consists in identifying a set of key dimensions for RCI and using them to review a body of relevant work, which can serve not only as a preliminary state-of-the-art for further reference, but also to give a more complete view on what is RCI and which is its research landscape.

The contributions of our paper can therefore be summarized as follows:

- we design a thorough methodology to identify RCI as an area of research;
- we define a set of dimensions for analyzing works in the RCI area;
- we provide a review of the state of the art in RCI;
- we give a description of RCI and its main characteristics, for further reference;
- we present the key research challenges, main areas and research landscape in RCI.

¹ <https://www.starship.xyz>.

² <http://flyinghighchallenge.org/>.

³ <https://avsincities.bloomberg.org/>.

⁴ <https://www.bbc.co.uk/news/technology-44068637>.

⁵ <https://tinyurl.com/ycmehvgr>.

In the remainder of the paper, we present the research methodology that was adopted (Sect. 2), followed by the analytical framework used to review the state-of-the-art (Sect. 3), which is then surveyed in Sect. 4. Section 5 summarizes our findings, draws the main characteristics and challenges of RCI, and describes its research landscape. Conclusions and general remarks are presented in Sect. 6.

2 Research Methodology

Based on the methodology for literature search described in [105], our survey consists in defining first the core terminology of our work, as well as the search and selection criteria to be used (rest of this section), then presenting the analytical framework (Sect. 3) through which the literature can be analyzed and synthesized (Sect. 4), and finally describing the area of Robot–City Interaction with its characteristics and its research landscape (Sect. 5).

2.1 Core Terminology

Here, the main terminology of our work (the terms *city*, *robot* and *interaction*) is explained based on the relevant literature.

Cities and modern cities We define a city as “a reasonably large and permanent concentration of people within a limited territory [...] concentrating commercial, administrative, industrial, cultural and other functions” [58]. In such territory, or *urban space*, three factors are essential:

- a large, culturally heterogeneous **population**, which is densely settled and bound in a municipality [36];
- the **relationships** held among the population, which change from being primary (familiar and neighborhood-related) contacts to being secondary/tertiary (impersonal, formal and bureaucratic contacts) [111];
- the **facilities** established by or for the population, i.e. “the fixed site, the durable shelter, the permanent facilities for assembly, interchange and storage; the essential social means are the social division of labor, which serves not merely the economic life but the cultural processes. [...] The city in its complete sense, then, is a geographic plexus, an economic organization, an institutional process, a theatre of social action, and an aesthetic symbol of collective unity.” [73].

In this definition we also include the *smart cities*, a new urban innovation paradigm which has emerged in the last years driven by the motivation that technology advancement could enable solutions to make cities more efficient and sustainable. Smart cities are cities that use networked infrastructures to improve economic and political efficiency and enable social, cultural and urban development [43], in which the kind of

technologies used, the scenarios in which they can be applied and the high diversity and distribution of data sources is the main novelty [21].

Autonomous robots A generic definition of robots is employed in our work, i.e. any active, artificial, physical agent whose environment is the physical world, which makes decisions on its own, guided by the feedback it gets from its sensing apparatuses [84]. We aim at investigating which robots could live in, engage with and benefit from a city ecosystem. In other words, we consider a robot as an agent with **sensing** capabilities, some **levels of autonomy**, and operating in a (surrounding) **environment**.

Interactions In general, interaction can be defined as “an occasion when two or more people or things communicate with or react to each other”,⁶ therefore stressing the importance of a **reciprocal effect** between its participants. In computer science, this reciprocal effect is mostly represented as information flowing from an artefact to a user and vice versa, e.g. Human–Computer Interaction and Human–Robot Interaction⁷ [50]. Based on this, we define interaction as the reciprocal influence that robots and city systems have upon each other or, in other words, the set of communications, connections, actions that exist in scenarios where both robots and the city infrastructures are involved.

2.2 Search and Selection Criteria

First, the literature was searched according to *dates*, *area* and *keyword* criteria described in the following.

Apart from a few notable exceptions that were included in the analysis, there is little work related to robots operating in modern cities before the year 2000. Hence, the search was restricted to the time-span between 2000 and 2018.

We then explored areas that we considered could be treating one or more aspects of Robot–City Interaction. These can be roughly divided in three big (but not exclusive) areas, namely Robotics, Information Communication Technology and Computer Science. In the first area, we considered works on social robotics, cognitive robotics, aerial robotics, Human–Robot Interaction and Cloud Robotics. In the second area, we found works oriented towards problems of ubiquitous computing, sensors and sensor networks, internet of things, computer vision or ambient intelligence. In the last group, we considered work oriented to data management, artificial intelligence, data mining, machine learning, cognition and knowledge engineering.

We searched for papers combining words such as “robots/autonomous systems/autonomous (mobile) agents” with words such as “city/cities”, “smart city/smart cities”, but

also any sub-system of a city including, for instance, “road/crowd”, “urban”, “pedestrian/citizen”, “water/pipes” etc.

Works were extracted both using Google Scholar and directly scanning journals and special issues (Intelligent Assistive Robots, International Journal of Robotic Research, International Journal of Social Robotics, Sensor Journal, to name a few) and conferences/workshops proceedings (e.g. robotics conferences as IROS, ICRA, AAMAS, RSS, HRI, and ubiquitous computing conferences as UBIComp, ISC, SMARTGREENS) related to the areas described above. Both forward and backward search was used to look for further candidates, along with the scan of the bibliographies and related work of the already selected works. Using this methodology, we were guaranteed to analyze a sufficiently large spectrum of work to ground our study.

Finally, the relevance of the works with respect to RCI was assessed by four judges, i.e. a work was considered if at least two of the following conditions applied:

- (1) *Urban robots* the work involves robots operating with some levels of autonomy in a urban space—a social space including a population involved in commercial, administrative, industrial or cultural activities (as per definition of Sect. 2.1);
- (2) *Smart infrastructures* the work focuses on the technological integration of robots in a city ecosystem, and more particularly there is an aspect of data exchange between robots and the city infrastructures;
- (3) *Open-ended interactions* the work studies robots operating in a highly-dynamic context involving interactions of different kinds, and where proactivity in decision-making is necessary to deal with an unforeseeable number of situations.

This guaranteed to clearly limit our selection to cases relevant to RCI, e.g. robots interacting with the crowds or operating in crowded environments, service robots in smart homes/hospitals/public spaces exchanging information with the city system, security/maintenance robots or driverless cars deployed by centralised infrastructures, while excluding hybrid cases such as intelligent environments, surgical robots, industrial manipulators and robot assisting elderly in their homes (unless an interaction with a city system was verified). Moreover, multiple references to the same project have been considered only if presenting a substantial difference, and discarded in the opposite case.

The final selection, available in Table 3 of Appendix at the end of this work, consists of 67 papers providing a preliminary state-of-the-art in the area of Robot–City Interaction.

⁶ <http://dictionary.cambridge.org/dictionary/english/interaction>.

⁷ See also Human–Machine Interaction and Animal–Computer Interaction.

Table 1 Summary of the RCI analytical framework

Agent context						
Robot type	Non-moving	Humanoid	Wheeled		Aerial	Marine
Robot actions	Navigation	Perception	Management	Manipulation	Verbal Communication	Acquisition
Level of autonomy	Low		Medium		High	

Urban context						
City actuators	Land		Citizens	Government	Technology	
City domains	Living	Economy	Governance	Mobility	Environment	People

Information context						
Data volume	Megabytes		Gigabytes	Terabytes	Pentabytes	
Data velocity	Batch		Periodic	Near-time	Real-time	
Data variety	Unstructured		Semi-structured		Structured	
Data Openness	Restricted			Open		

Interaction context						
Robot-Citizens	Intimate		Personal	Social	Public	
Robot-Land	Exhibit		Passage	Special use	Secure	Backstage
Robot-Government	Yes			No		
Robot-Data	Acquisition		Processing		Dissemination	
Robot-Robot	Heterogeneous team		Homogeneous team		Single-robot team	

3 The RCI Analytical Framework

The analytical framework takes inspiration from semiotics theories aiming at studying how interactions are affected by the social and physical spaces in which they happen [92]. Main insights behind these approaches are the idea that studying an interaction involves more than the players that take part into it (e.g. the nature of the interaction itself or the scope of it), and that the physical space is a key element to interpret interactions. This presents an interesting overlap with the main concepts of RCI, as we have defined in Sect. 2.1.

Inspired by such theories, we identified the key aspects of works to be analysed (we call these *dimensions*) in light of established background literature, and then grouped them thematically according to four *contexts*. Such contexts, presented below, aim at describing not only the three players of RCI (the robots, the city as a complex ecosystem and the information they exchange), but also the nature of the interaction that is happening between them:

1. *Agent context* Dimensions describing characteristics specific to the autonomous agents acting in and with a city, e.g. the type of robots or their capabilities.
2. *Urban context* Dimensions characterizing the city as a set of connected infrastructures providing services to the citizens.
3. *Information context* Dimensions describing the information exchanged between the autonomous agents and the city, i.e. the nature of the communicated data.

4. *Interaction context* Dimensions characterizing the interactions between autonomous agents and single city systems, e.g. the citizens or the governance.

A summary of this framework is presented in Table 1.

3.1 Agent Context

As previously mentioned, the first analysis concerns aspects describing the autonomous agents that take part into in RCI scenarios. We consider here 3 dimensions: robot type, robot actions, level of autonomy.

Robot type This dimension aims at analyzing the type of robot that is employed in a Robot–City Interaction scenario. A reference work on the classification of robot types is [91], which categorizes robots as:

- *ground, non-moving robots* platforms with movable components such as the Baxter platforms;⁸
- *ground, moving, human-like robots* legged, humanoid or human-like robots such as Pepper,⁹ ASI-MO,¹⁰ or the Boston Dynamics suites;¹¹
- *ground, moving, wheeled robots* robots provided with wheels, such as the Starship deliverers, the Robotnik

⁸ <https://www.baxter.com/inside-baxter/about/overview/corporate.page>.

⁹ <https://www.ald.softbankrobotics.com/en/robots/pepper/>.

¹⁰ <http://asimo.honda.com/>.

¹¹ <http://www.bostondynamics.com/index.html>.

Summit suites¹² or Komodo,¹³ which are not necessarily human-like;

- *aerial robots* drones provided with rotors, such as the Erle Robotics's copters¹⁴ or the Parrot drones;¹⁵
- *marine robots* vessels used for underwater activities such as the Searobotics suite.¹⁶

Robot actions Here, we focus on which actions are mostly performed by robots in Robot–City Interaction scenarios. We consider high-level actions, re-adapted based on the work of [98]:

- *navigation* the fundamental act of moving from point A to point B;
- *perception* the act of perceiving and understanding the environment through sensing and interpreting sensory data;
- *management* the act of coordinating and managing the actions of humans and robots, acting independently or in groups;
- *manipulation* the act of interacting with the environment through body-part movements, hence including body-part movement;
- *verbal communication* the act of interacting with the social world using the past experience, exhibiting social competencies;
- *acquisition* the act of interacting with the physical world acquiring new competencies.¹⁷

Levels of autonomy This dimension aims at analyzing which degree of autonomy the agents taking part to a Robot–City Interaction scenario exhibit. Defining autonomy represents a complex problem itself, and many taxonomies have been presented in the literature [6,35,93]. We chose therefore to adopt a simplified scale (from low to high) to describe the autonomy of the agents operating in RCI scenarios, and leave as future work the task of providing a more complete categorization. We invite the reader to refer to the cited works as further reference for the terminology. The scale ranges as follows:

- *low autonomy* includes the lowest levels of robot autonomy, e.g. manual, tele-operation and assisted tele-operation, in which the aspects of a task to achieve (e.g.

sensing, planning, acting) are fully or partly performed by a human;

- *medium autonomy* includes the range of batch processing, decision support and shared control (with or without robot initiative). Generally speaking, the robot performs its tasks autonomously, and the support of an external agent goes from narrowing the set of tasks, to determining the goals and to monitoring the execution;
- *high autonomy* includes the highest levels of robot autonomy, e.g. executive control, supervisory control and full autonomy, where sensing, planning and acting are performed by the robot under or without external control.

3.2 Urban Context

The second context includes aspects describing the city as a complex system of infrastructures.

City actuators The city actuators are the components involved in a city system, but not necessarily included in its actual implementation [19]. This dimension aims at analyzing which actuators of the city are mostly involved in (or are more benefitting from) a robot–city interaction. We consider the following actuators:

- *land* the geographical area where robots are operating;
- *citizens* the people involved, operating or benefitting from a robot–city interaction;
- *government* the public administration appointed by the citizens, which will benefit from the interaction e.g. improving its services;
- *technologies* the infrastructure and services enabling the robot–city interaction.

City domains In order to analyze which city components (e.g. water and energy systems, roads and transportation networks etc.) are involved in a robot–city interaction, we categorize these according to a set of city domains, that are well-established in the smart city literature [32]:

- *economy* activities promoting to the innovation, entrepreneurship, economic growth and productivity to enhance competitiveness;
- *people* activities promoting the citizens' education, plurality, flexibility, creativity, cosmopolitanism, and participation in public life to enhance the social and human capital;
- *governance* activities enhancing the citizens' participation, public and social services and transparent governance;
- *mobility* activities to improve the management systems for urban traffic, local and international accessibility, and safety to enhance the transports infrastructure;

¹² <https://www.robotnik.eu/>.

¹³ <http://www.robotican.net/komodo>.

¹⁴ <http://erlerobotics.com/>.

¹⁵ <https://www.parrot.com/uk#drones-fpv>.

¹⁶ <http://www.searobotics.com/>.

¹⁷ Originally considered as *social interaction* by [98], we believe that “verbal communication” and “acquisition” should be considered separately due to the variety and complexity of city scenarios.

- *environment* activities to improve energy efficiency, sustainable resource management and environmental protection to protect natural resources;
- *living* activities to enhance the citizens' quality of life through cultural facilities, health conditions, individual safety, housing quality.

3.3 Information Context

The third context concerns the description of the type of information that is exchanged between robots and cities when interacting. Since the goal of the study is to analyze how autonomous agents are deployed in cities that rely on modern technologies, we describe such information in terms of data exchanged during a robot–city interaction. Due to the large information needs of robotics systems, we consider here information produced by the robots' internal sensors as well as information produced by external sensors, provided that these are exchanged as part as the city infrastructure. The dimensions here considered are selected based on the four data dimensions typically used in Data Science [12].

Data volume The volume of data refers to its magnitude. This dimension aims at analyzing the quantity of data generated, stored or simply involved during an interaction between robots and cities. We consider:

- *megabytes* e.g. tables and files;
- *gigabytes* e.g. transactions;
- *terabytes* e.g. datasets and records;
- *pentabytes* e.g. large real-time data collections.

Data variety Variety is referring to the structural heterogeneity of the data. This dimension aims at analyzing the type of data mostly used, namely how diverse is the information exchanged. Such diversity is categorized as:

- *unstructured data* such as texts, images or audios;
- *semi-structured data* unstructured data annotated using markup languages (e.g. XML);
- *structured data* i.e. as tabular data, XML files, JSON streams, or relational databases;

Data velocity The velocity of data refers to the rate at which data is generated, changed, processed and exchanged. We study here if robot–city interaction works mostly use:

- *batch* communication of data;
- *periodic* communication of data;
- *real-time* communication of data.

Data openness In the context of RCI, the openness of data is a crucial aspect and might be preferred to data veracity, which is often used to determine the data trustworthiness.

With this dimension, we are interested in understanding the data sharing aspect, i.e. whether knowledge is privately exploited or rather (fully or partly) shared. We analyze the RCI scenarios based on two possible values:

- *restricted* if they only make use of privately accessible data;
- *open* if they include some available external information such as openly accessible data.

3.4 Interaction Context

The last context concerns those aspects which describe the interaction between robots and the single components of a city, namely the land, the citizens, the government and the technologies.

Robot–citizens interaction Here, we aim at describing how the robots interact with the citizens. For this, we can use Hall's proxemic spaces [37], which allow us to identify the interpersonal distance at which such interactions happen. Each space is then combined with the operations that can be performed in that space, as proposed by [47]:

- *intimate space* (0 to 0.45 m ca.) the closest space to the self. Allowed actions span from approaching to touching.
- *personal space* (0.45 to 1.2 m ca.) generally reserved for interactions with friends and family. Allowed actions include following, approaching and touching.
- *social space* (1.2 to 3.7 m ca.) for interactions among acquaintances. Allowed actions include passing, following and approaching.
- *public space* (from 3.7 m): for public speaking interactions. Allowed actions range from none (robot and citizens not interacting at all), to avoiding and following.

Robot–land interaction We look into analyzing which is the type of physical spaces in which a robot–city interaction happens. We consider two basic types of spaces as defined by [34], namely frontstage (open to the public) and backstage spaces (closed to the public). The first ones are then additionally sub-divided based on the type of activities that can be performed, resulting in the following classification:

- *exhibit spaces* frontstage places that are created to be looked at and passed through without altering them (e.g. public squares);
- *passage spaces* frontstage places designed for the movement and passage from a space to another (e.g. streets or pathways);
- *special use spaces* frontstage places reserved for a particular activity (e.g. restaurants, smoking areas);

- *secure spaces* public and controlled areas, such as a hospital, a school, an airport;
- *backstages* private spaces that only allowed people with a key/pass/password can access (e.g. a house).

Robot–government interaction This dimension aims at analyzing the level of engagement of the city administration, e.g. if robots are deployed to demonstrate good city governance, if they cooperate with the city public services through data exchange/task allocation, etc. We consider here:

- *yes* if robots are appointed by the government or its services, or are contributing to improving them;
- *no* in the opposite case.

Robot–data interaction This dimension aims at analyzing how robots deal with data from the city, which actions they can perform, how and if they can manage the heterogeneity of datasets, etc. Common patterns on the activities that can be performed on data in a urban context can be found in the literature [18,96]:

- *data acquisition* all the activities for collecting, checking the quality, filtering and describing new data.
- *data processing* activities to process, manipulate and analyze the collected data, with the aim of generating new information supporting some data-related tasks;
- *data dissemination* activities targeted to disseminate, deliver and share the processed information to external systems and end-users.

Robot–robot interaction This dimension describes the interaction that robots can have with other robots. In particular, we aim at exploring at which level the robot–city interactions involve team cooperation (if any), defined by [114] as:

- *heterogeneous team* if a team is composed by different types of robots;
- *homogeneous team* if a team involves the same type of robots;
- *single-robot team* if only one robot is considered (therefore there is no robot–robot interaction).

Given the described framework, the following section summarizes the selected literature according to each presented dimension.

4 Literature Synthesis

In this section, we summarize the selected works to provide an initial state-of-the-art in the area of Robot–City Interaction

and to identify the current gaps of the area. After providing a synthesis based on the four contexts defined in Sect. 3, we give some conclusions based on the RCI areas that were identified during the process. As previously mentioned, all generated data (selected papers and dimensions identified for each of them) can be examined in Table 3 of Appendix at the end of this work.

4.1 Synthesis by Context

The RCI dimensions are discussed in this Section from the perspective of the four analytical contexts (i.e. the *agent*, *urban*, *information* and *interaction* context).

4.1.1 Agent Context

In terms of the type of robots employed in RCI works, Fig. 2 shows that wheeled or humanoid robots are mostly involved.

Wheeled non-humanoid platforms are more common, as these are often built ad-hoc, hence cheaper and more customizable; as for humanoid/legged platforms, these tend to be more specific to group–robot interaction scenar-

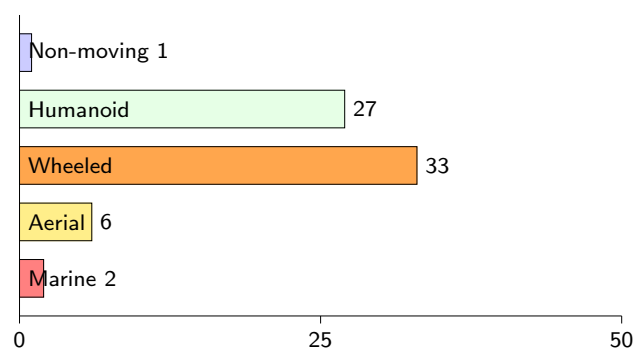


Fig. 2 Most common types of robots in RCI

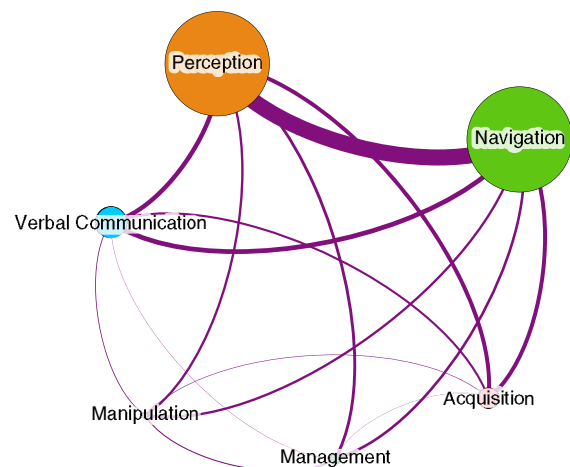


Fig. 3 Robot actions (the nodes) and how frequently they co-occur (the edges)

ios [30,33,55,64]. This is likely due to the presence of the citizens, which might naturally be more inclined to share the urban space with human-friendly presences. Aerial platforms—employed both as single units [16,26,28,76] and in combination with other platforms [60], are less common, likely due to the rather recent emergence of drones as reliable platforms, as well as to the regulations currently restricting their usage in public spaces.

The ability of robots to perform different actions is analyzed in Fig. 3 using the network partitioning technique, which allows to analyze the importance of categories in pairs (i.e. how often they occur together). In the specific, robot actions are represented as nodes varying in size depending on their frequency, while the size of the edges indicates a robot's ability to perform two actions (i.e. the source and target of the edge)—for example, a robot that can perceive and navigate.

Along with the current research trends, navigation and perception are shown to be prominent in RCI, too. The strong co-occurrence between them mostly derives from the fact that perception is naturally required to navigate, which is a fundamental requirement for most of the applications. Indeed, many of the selected works focus on advanced navigation algorithms combined with state-of-the-art sensor technologies [29,38,56,57,62,90]. Verbal communication and acquisition, which are medium-sized in the figure, are also somewhat common: This happens mostly in contexts where robots are required to interact with the citizens to achieve their goals, as in [30,39,45,53,69,87]. The ability of management is mostly employed in combination with perception and navigation—typically scenarios involving more than one robot, e.g. such as monitoring spaces for security or traffic management purposes [5,40,51,60,61,110,112].

Figure 4 shows the robot autonomy level in the analyzed works. While a rather equal distribution can be observed, the literature reveals that the level of autonomy very much depends on the application domain. Robots with medium to high-level autonomy are mostly required in outdoor sce-

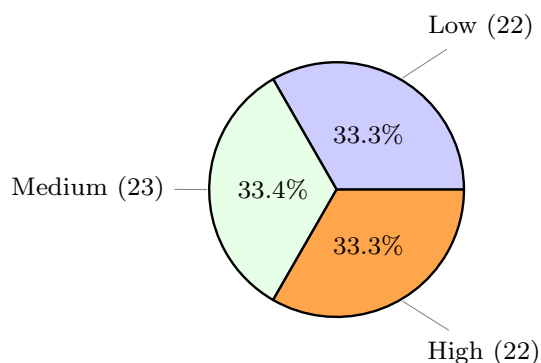


Fig. 4 Autonomy of robots in RCI scenarios. Values of this category are exclusive

narios where the human presence is not necessary, such as driverless cars [3,25,40,51,61,110,112] and infrastructure maintenance [17,41,59,67,76,86,89]; on the contrary, a low to medium level of autonomy is observed when citizens are involved, both through public engagement [13,22,30,49,53,87,88,109] and personal assistance [10,39,45,69,83].

4.1.2 Urban Context

We summarize here the urban dimensions considered in Sect. 3.2, i.e. the city actuators and the city domains that mostly take part to the robot–city interactions.

In Fig. 5, we use network partitioning to analyze which city actuators (i.e. components) are mostly involved in a robot–city interaction. Nodes are sized according to how often an actuator was taking part to an interaction—be it a target, promotor or a mean through which the interaction happened; edges are weighted according to how often the two actuators have been observed together. We observe that technologies, intended as the ICT infrastructures employed by a city to better manage its own resources, are largely involved, as demonstrated by their node size and by the strong (thicker) connections they have with government, land and citizens. Interestingly, a large role is also played by the government, showing that many of the scenarios in RCI are intended to improve the services offered by the city. Citizens and land tend to be less involved in RCI, as the weaker connections with the other city actuators demonstrate.

Similarly, Fig. 6 presents the city domains in which robot–city interactions mostly take place. Governance has a central role here, combined with either the people's well-being, the environmental infrastructure or the mobility services. This is also congruent with increasing efforts that governments and municipalities are putting into technological advancements, see initiatives such as the smart cities. As for the domain of living (intended as people's well-being), few records of an interaction are reported. This shows that, despite the advancements of areas such as the Internet of Things, Ambient Intelligence or Ambient Assisted Living, scenarios in which

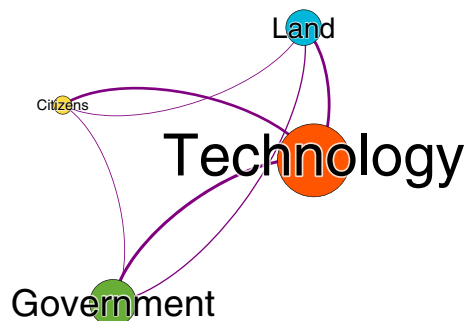


Fig. 5 The actuators of an interaction in RCI scenarios (nodes), and how often two actuators interact (edges)

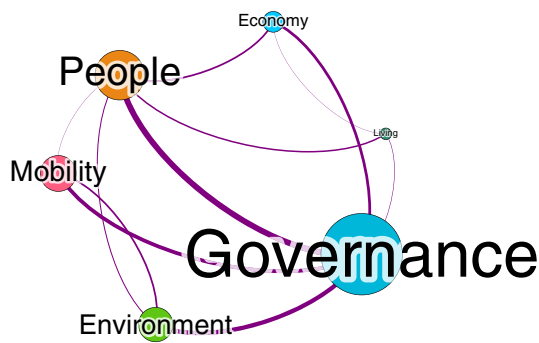


Fig. 6 Domains of a city that are mostly involved in RCI scenarios: a central role is observed for governance

smart homes interact with city administrations seems yet to be realized.

4.1.3 Information Context

The dimensions of Sect. 3.3 analyze the nature of the data exchanged in RCI. Note that categories here are not exclusive, and the robots’ own sensor data are considered only if exchanged within the city infrastructure.

Figure 7 shows that RCI scenarios involve low quantities of data, mostly MB and GB (indeed, we reported no cases of TB or PB of data exchanged). This represents a considerable difference w.r.t. sensor networks, big data and smart cities scenarios, in which data infrastructures manage tera- and petabyte-sized datasets [54]. With that said, such infrastructures often have difficulties in managing data at high rates [115], while the data exchange in RCI does happen at a fast rate, as demonstrated by the large percentage of systems exchanging data in real-time (cfr. Fig. 8).

Figure 9 shows that unstructured and semi-structured data are exchanged in the majority of RCI scenarios (vs. few cases using structured data, e.g. [22,40,65,90,110]). This

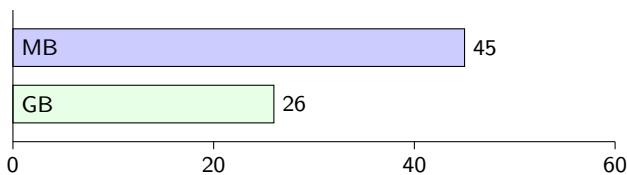


Fig. 7 Volumes of data exchanged in RCI

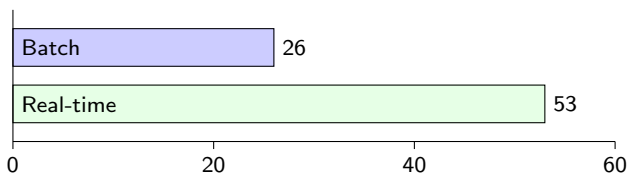


Fig. 8 Velocity at which data are exchanged in RCI

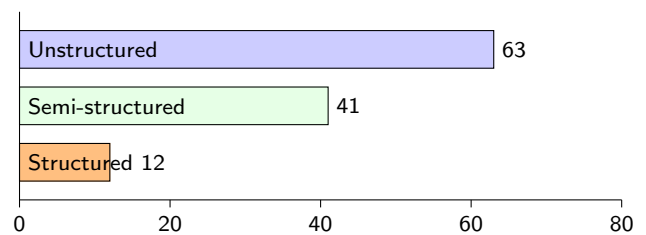


Fig. 9 How diverse are data exchanged in RCI

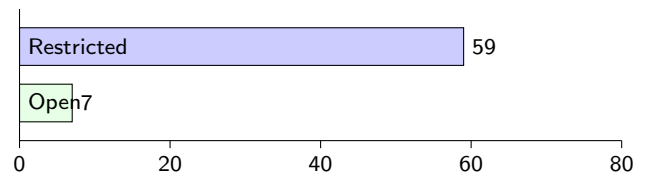


Fig. 10 Usage of open (public) and restricted (private) data in RCI scenarios

reveals that providing a more semantic representation of the data exchanged is still of little emphasis in RCI, as works tend to focus on building ad-hoc cyber-physical systems [5,10,26,83], where robots are often seen as mobile sensors rather than knowledge producers [60,62,79,81]. This also conforms with the fact that robotics lacks of established standards and best practices for data representation and exchange, while these have been proven to be fundamental in promoting interoperability in applications involving heterogeneous systems (e.g. the Internet-of-Things [74]).

Finally, Fig. 10 shows that, besides the ongoing efforts of openly sharing knowledge from different sources, very few works in RCI [5,17] have indeed explored the potential of open data to solve their problems.

4.1.4 Interaction Context

Here, we aim at understanding how and how much robots interact of the city ecosystem in terms of its single components (i.e. citizens, land, government, technologies).

From the perspective of the relationships between citizens and robots, Fig. 11 reveals that a majority of interactions happen in public spaces, typically in works tackling planning and navigation issues [3,25,40,41,51,61,86,110,112]. In this sense, citizens are mostly seen as variables of a highly dynamic environment, which have to be considered equally to other obstacles. With that said, closer interactions of a social or personal nature are also common, namely in scenarios involving citizens for private or public assistance [10,13,30,49,53,83,87,88,109].

Figure 12 show how robots interact with their surrounding geographical space (the land). Expectedly, backstage spaces are less common in RCI scenarios, followed by secure spaces and special spaces such as hospitals [39,103], construction sites [76,86,89] and underground city infrastructures [48,75].

Publicly available passage and exhibit spaces are overall more common, specifically in outdoor scenarios.

Figure 13 reports that few works have some form of robot–government interaction, typically in cases in which robots are employed by the public administration as a support for security or maintenance [16,26–28,79,81,107].

Figure 14 shows that robots mainly acquire and process data from the city, while dissemination (being more time-consuming) is less common [16,17,79,81,107], and mostly employed when teams of robots are involved.

Finally, Fig. 15 shows how a large amount of RCI works employ robots as single units. This is mostly due to the task-allocation difficulties arising when integrating several robots in a large-scale scenario. Indeed, teams of robots seems to be used in more controlled contexts, such as road navigation, city infrastructure maintenance or city security.

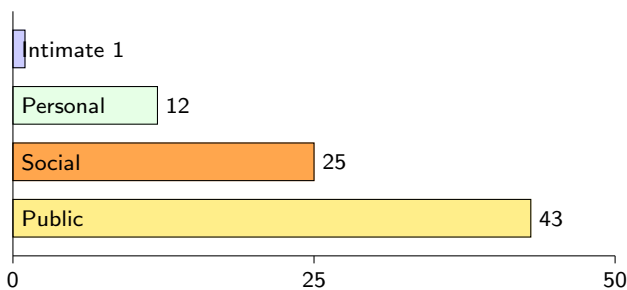


Fig. 11 Types of interaction between robots and citizens

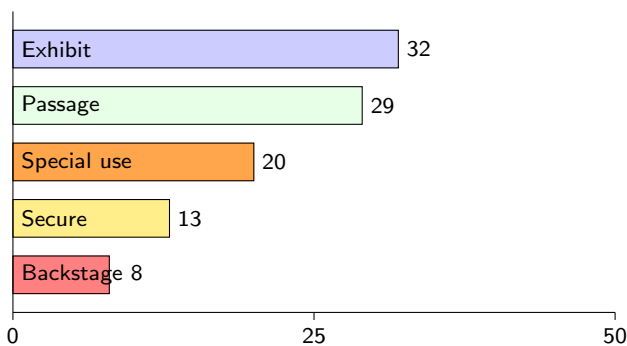


Fig. 12 Spatial nature of the robot–city interaction in the observed works

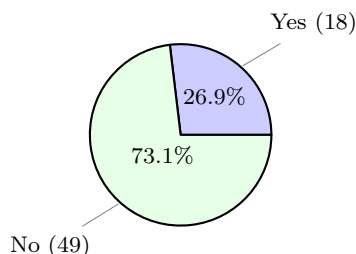


Fig. 13 Interaction between robots and government. Values of this category are exclusive

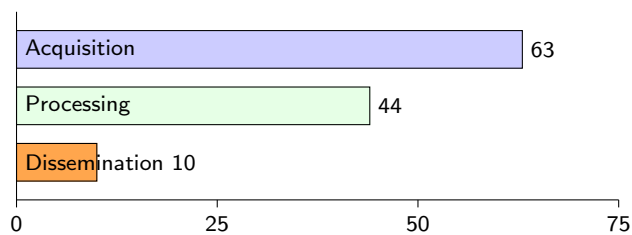


Fig. 14 Actions performed on city data by robots

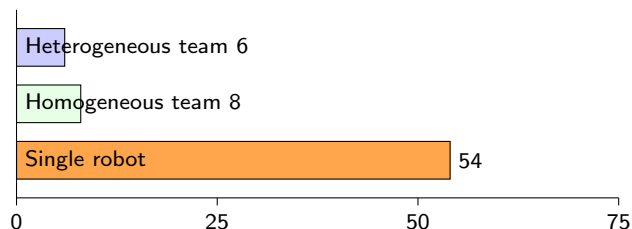


Fig. 15 How robots interact between each other in urban scenarios

4.2 Synthesis by RCI Area

One of the main considerations to be drawn from the previous section is that a series of patterns have emerged during the analysis, which allow us to group the reviewed papers according to the aspects and characteristics they share. We grouped the literature in six macro-areas, which we have identified as: Urban Security (US), Citizen Assistance (CA), Public Space Engagement (PSE), Mobility in Urban Dynamic Environments (DE), Autonomous Urban Transportation (AU) and Urban Maintenance (UM). These areas are helpful not only to have a better view over the main RCI themes, but also to understand more precisely specific characteristics and open challenges. We invite the reader to use Figs. 16, 17, 18 and 19 as support and reference for the description of each area. Also, it is worth mentioning here that many works might naturally overlap but, for the sake of simplification, they are presented as belonging to one area only.

4.2.1 Urban Security

Urban Security is the area focusing on techniques and methodologies to embed robotics systems into the city’s security infrastructures. Examples of urban security applications can be, for instance, urban search&rescue (USAR), crime prevention, emergency/parking management and monitoring. These require state-of-art sensor technologies (e.g. radars, laser scanners), advanced management of data infrastructures, visual techniques for object detection, and performant algorithms for autonomous navigation, task allocation and planning.

We found in this area works focusing on the collaboration between robots and city services with the aim of supporting the citizens during an emergency [26,44,107],

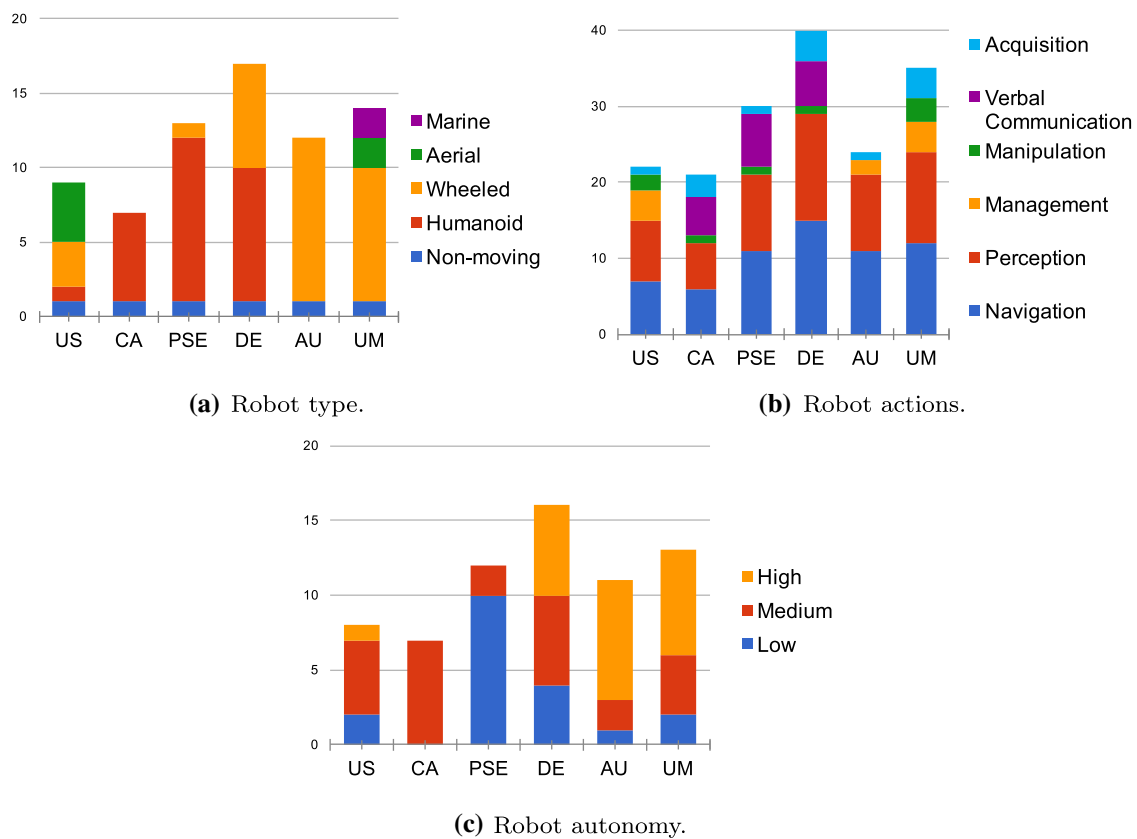


Fig. 16 Agent context organized by RCI area

intelligent designs of networked infrastructures that integrate robots [27,28,78,81], and planning/ decision-making solutions for monitoring situations such as parkings or road networks [16,79].

As reported in Figs. 16, 17, 18 and 19, works in urban security present the following characteristics:

- highly mobile platforms such as UAVs and wheeled robots, which are able to precisely perform outdoor navigation, environmental perception and manage a situation;
- robots operating mostly autonomously, sometimes partially supervised by humans;
- central role of the government as an actor w.r.t. land/citizens, as well as the governance and the citizens’ well-being representing the city aspects mostly studied;

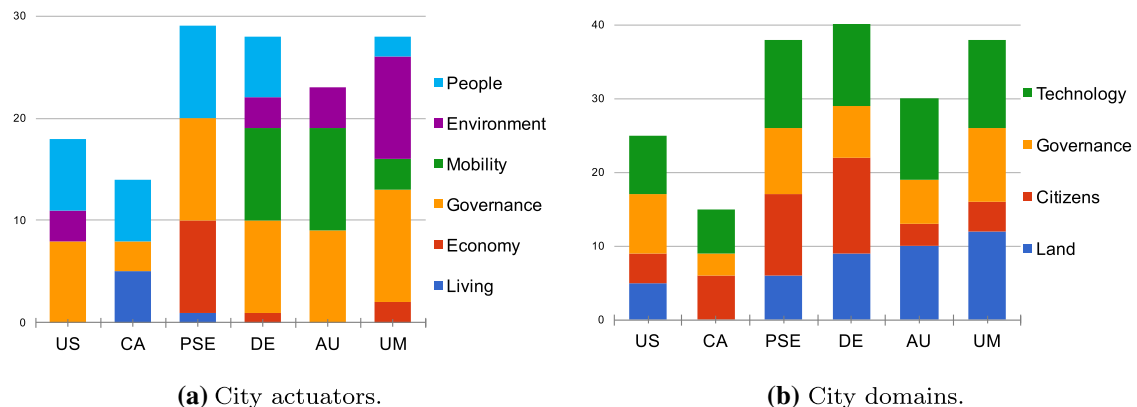


Fig. 17 Urban context organized by RCI area

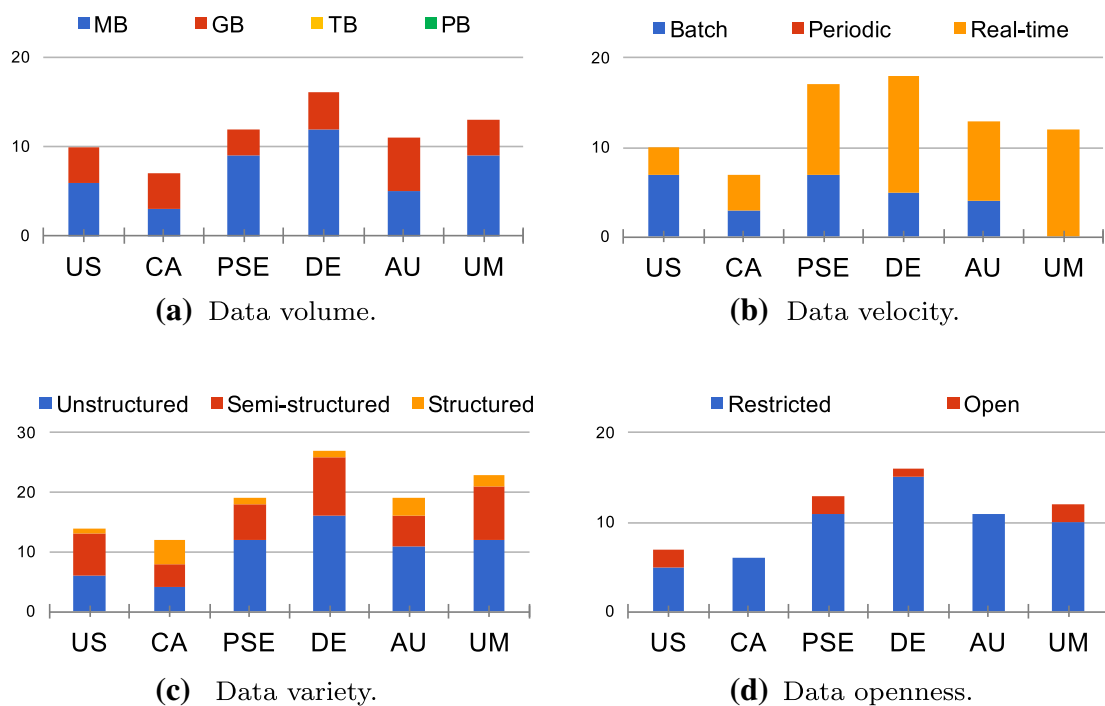


Fig. 18 Information context organized by RCI area

- low quantities of (mostly) raw and semi-structured sensor data communicated;
- communication of data both in batch and periodically, e.g. if an emergency is detected;
- some usage of open data, e.g. OpenStreetMap¹⁸ in [28];
- personal to public interactions between robots and citizens, generally in public spaces such as exhibit or passage places;
- high cooperation between robots and the city municipality;
- robots able to acquire, process and share knowledge, generally operating in a team rather as a single element.

4.2.2 Citizen Assistance

This area comprehends applications of robots employed to carry out public assistive services for the citizens. Methods and technologies from Ambient Assisted Living, sensor networks, Cloud Robotics and HRI are combined in order to present solutions that aim at improving the citizens' quality of life, either in their homes or in spaces providing assistive services (e.g. hospitals).

Works in this area range from intelligent systems and software architectures testing and simulating how robots communicate with intelligent environments [55,103] and perform assistive-specific tasks [10,83], to real-world appli-

cations where mobile platforms are continuously operating autonomously [39,45,69].

The main characteristics observed in this area are:

- wheeled and humanoid platforms with a medium autonomy, both due to the close contact with the citizens;
- basic capabilities of navigation and perception, essential verbal communication, partial acquisition capabilities aiming at a more personalized interaction with the citizens;
- involvement of the government as an actor, in combination with the citizens and technologies, while the land actuator is of secondary importance;
- focus on the people and living city domains, and lower interest in the economical, environmental and mobility ones;
- exchanged data low in volume (mostly MB), communicated both in batch (when receiving a user input) and real-time (through the perceiving sensors);
- employment of unstructured, semi-structured and structured data, but no usage of open data;
- essentially personal interactions between citizens and a single mobile agent, mainly happening in spaces with restricted access (backstage places such as houses, and secure/special use spaces such as hospitals);
- no robot–government interaction;
- data acquisition and processing capabilities, and little ability to disseminate (and share) data.

¹⁸ <https://www.openstreetmap.org>.

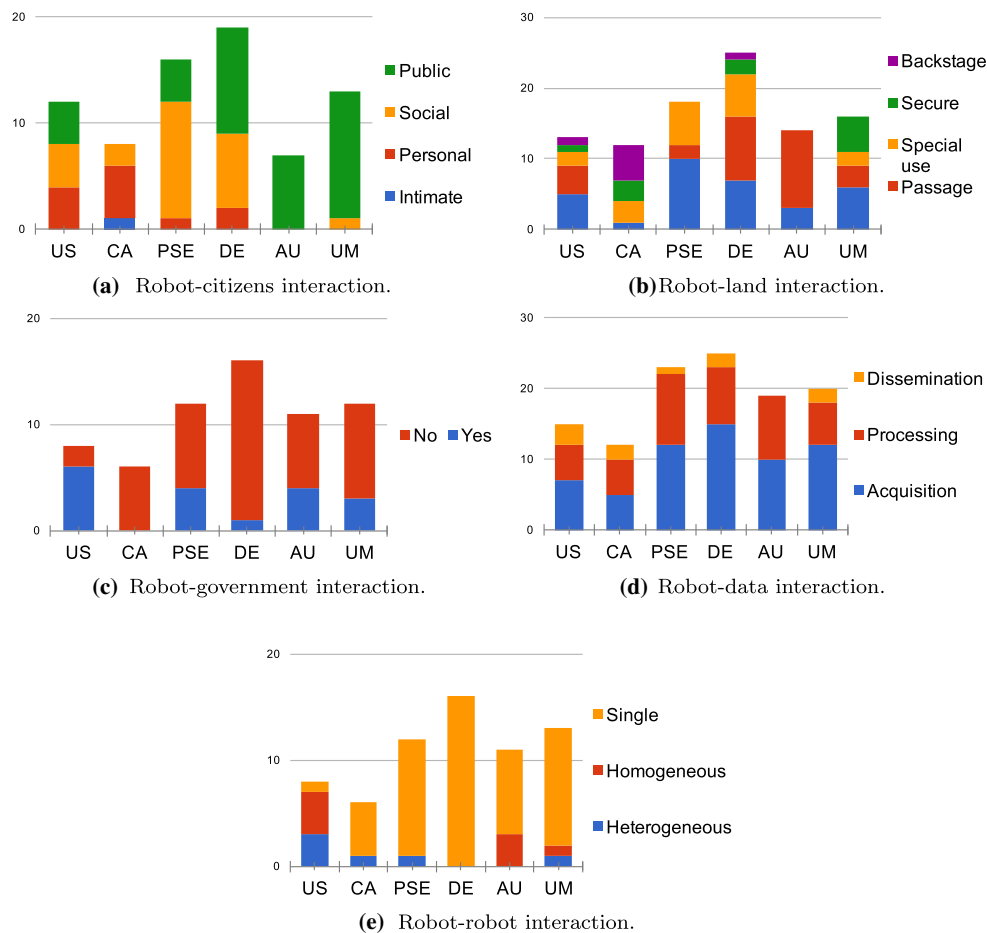


Fig. 19 Interaction analysis organized by RCI area

4.2.3 Public Space Engagement

Public Space Engagement is the area focusing on employing robots in everyday social environments (for example, public squares, museums and shopping malls) and on studying how robots socially and ethically interact with the citizens. Techniques from ubiquitous computing, wireless sensor networks, HRI and social science are employed to study both a wide range of aspects, from infrastructure and networking, to ethical and social acceptance.

Works here can be divided into architectures and frameworks allowing interaction between robots, humans and ubiquitous sensors [33,68,94], and works aiming at analyzing the public engagement and social acceptance, either on demand [30,53,87,109], or through personalization [22], or directly using the robots' proactivity [13,49,88].

We observe here the following characteristics:

- wheeled and humanoid platforms, where navigation, perception and communication abilities are essential. In

some cases, manipulation or acquisition are also supported (as in [13,88]);

- a low level of autonomy, due to the employment of robots in much larger, dynamic, and uncertain environments;
- large involvement of citizens, government and technologies in the interactions, and minor importance of the land;
- usage of autonomous agents to support the economical, municipal and well-being aspect of the city;
- low quantities of unstructured/semi-structured data exchanged, both in batch (if the system is queried) or in real-time (sensor data);
- some usage of open data in public contexts, as in [22,30];
- mostly social or public interactions, rare personal interactions;
- interactions happening in front spaces, both exhibit and special use spaces (e.g. public squares and museums);
- no robot–government interaction.
- mostly single robots are employed;
- data acquisition and processing capabilities, less investigation of data dissemination and knowledge sharing.

4.2.4 Mobility in Urban Dynamic Environments

In this area, we find research investigating how robots can interact with urban dynamic environment for pedestrian-like autonomous navigation. A wide range of techniques, spanning from perception, navigation and planning to image processing, are investigated here.

Works in this area focus on robot navigation in highly constrained indoor environments (e.g. a museum or an exhibition) [11,29,95,99] or outdoor areas, both autonomously [1,56,57], through interaction with the citizens if the space is unknown [23,64]. Other works focus on improving the simultaneous localization and navigation through the integration of some a priori knowledge, e.g. some pre-analyzed human behaviors [63,70,77,102] or knowledge from some external sources [7,65,80].

Observed characteristics here are:

- wheeled platforms (both humanoid and non), equipped with navigation, perception and (less often) verbal communication abilities;
- higher levels of autonomy;
- a larger (w.r.t. the previous areas) involvement of the land and citizens as actuators of the interactions, lower presence of the government;
- mobility and well-being of people being the most concerned city domains;
- low quantities of unstructured/semi-structured data exchanged, mostly in batch;
- little usage of open data (with exception of [11]);
- mainly social and public robot–citizens interactions;
- mostly social or public interactions, happening in exhibit, passage and special use spaces;
- little robot–government interaction (only reported in [63]);
- employment of mostly single robots, which do not necessitate data dissemination, due to the focus on performing advanced navigation.

4.2.5 Autonomous Urban Transportation

Autonomous Urban Transportation is the area concerned with using robot agents to monitor, control and manage the traffic and mobility of the city. The works in this area combine techniques for image processing, data collection, navigation and planning, with the aim of improving the performance of intelligent vehicles which can navigate in dynamic and uncertain environments.

We find here both works tackling problems of perception and sensing, e.g. how to navigate in hard conditions such as obstacles, rain, or fog [38,62,90,113], and works tackling problems issuing from coordination and knowledge sharing, including multi-vehicle coordination [3,40,51,110], citizen-

vehicle coordination [25,112] or traffic-based coordination [61].

More specific characteristics are as follows:

- highly autonomous wheeled platforms (typically, autonomous car-like), equipped with highly developed perception, navigation and (sometimes, see [25,40]) management capabilities;
- centrality of the land and technologies actuator, less priority given to both government and citizens;
- large focus on the mobility aspect of the city;
- data exchanged in low quantities, privately and in real-time;
- some efforts put in exchanging structured data [40,90,110];
- public robot–citizens interactions in passage spaces (roads and crossings);
- occasional robot–government interaction;
- data acquisition and processing are fundamental actions, dissemination of data is yet to be employed;
- mostly teams of the same kind of robots (e.g. vehicles) employed.

4.2.6 Urban Maintenance

Urban Maintenance is the area focusing on applying robotics solutions to maintain the city's distributed infrastructures. Enabling techniques in this case come from machine learning, ubiquitous computing, wireless sensor networks and motion planning.

We find in this area works focusing on the data acquisition problem to improve autonomous planning and navigation of outdoor machineries [17,41,76,86,89], works for environmental recognition [42,48,59,67,75] and works aiming at optimizing cooperation and resource consumption [5,60].

This area has the following characteristics:

- heterogeneous platforms types, from non-humanoid wheeled robots to marine/aerial robots;
- essential navigation, perception and management, sometimes paired with the capability of acquiring new information of the surrounding environment [5,17,59,67] or manipulating it [41,86,89];
- high level of autonomy;
- land, government and technologies as core participants of an interaction, less involvement of the citizens;
- governance and environments as the most concerned city domains, few cases considering the people's well-being [17] and economical aspects [41,86];
- low quantities of raw and semi-structured data exchanged generally privately and in real-time, few cases of structured or open data [5,17,89];
- mostly public robot–citizens interaction;

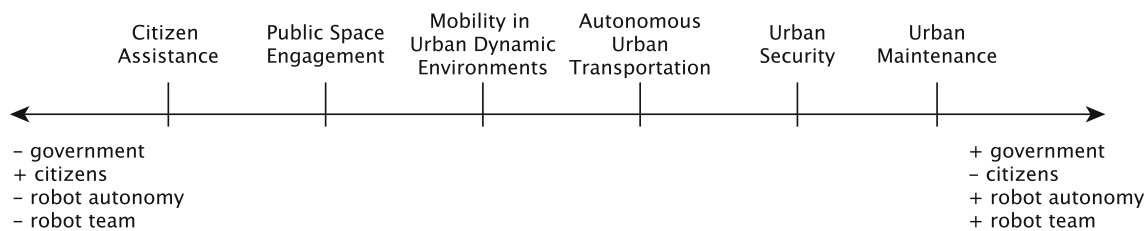


Fig. 20 Research areas of RCI

- robots operating essentially in front spaces, either as single units or homogeneous teams;
- some interactions between robots and government [17, 60];
- acquisition and data processing more employed than data dissemination.

The research areas of RCI here presented are shown in Fig. 20 based on the most evident characteristics, namely how much the government or citizens are involved, and what is the autonomy level of robots in the area and whether they operate mostly as teams of single units. An overall summary of the dimensions can also be seen in Table 2.

5 The RCI Research Landscape

Based on the analysis we conducted, we characterize in this section RCI as a multidisciplinary field, while providing a discussion on its research landscape.

5.1 Summary

Here, we look at answering the question: *what did we discover from our literature review, and how has our view changed since the beginning our work?*

The literature review confirmed our hypothesis that integrating robotics platforms into modern city systems is a complex problem, as induced by the variety of research areas involved. However, the growing interest on research topics involving robots in cities calls for an identification of the open problems under a unified perspective.

From our first analysis (the agent context of Sect. 4.1.1), we learnt how cities are currently integrating robots with advanced perception and navigation capabilities, thanks to the modern motion planning algorithms and sensing technologies. While the autonomy of the agents tends to vary depending on the research area, the type of robots which are mostly employed are ground robots. This is mostly due to three reasons: first, robust off-the-shelf ground robots are nowadays common, while highly performing non-ground robots are still prohibitive in costs, and therefore only

employed in controlled scenarios; second, the techniques at the state-of-the-art for ground robot mobility are much more advanced with respect to aerial and marine robots; third, current regulations limit the deployment of aerial robots and therefore experimenting with those in concrete settings is still problematic.

The analysis of the urban context (Sect. 4.1.2) confirmed our idea that the interest in integrating robot technologies in the city's ecosystems is growing, and showed how much the city actors and domains are being involved in the robot–city interactions. Advanced data and communication technologies, which are largely involved in RCI scenarios, allow the creation of solid city infrastructures, guaranteeing efficient robot–city interactions. Public institutions and governments, at the same time, encourage investments and initiatives in this area with the aim of improving their offer and services. The lack of balance in the way city actuators take part in robot–city interactions (e.g. citizens or land having a lower priority), as well as the small number of scenarios involving the economical and people well-being aspects, suggest what new directions can be undertaken in the near future.

Some interesting conclusions about the nature of the information exchanged between robots and city systems can also be drawn from the analysis of the information context in Sect. 4.1.3. Robots in RCI deal with small amounts of real-time, unstructured (sensory) data, which do not impose any model constraints. This constitutes a remarkable discrepancy w.r.t. how information is managed within modern city systems (see, for instance, the smart cities initiatives), where a high degree of organization is required to manage the heterogeneous information (both sensory and common-sense knowledge) gathered from different sources. Similarly, while one of the main aspects of smart cities is the usage of open data to promote knowledge sharing, the surveyed works seem to make mostly usage of proprietary or closed data.

The difficulty of sharing knowledge in RCI scenarios also emerges from the analysis of the interaction dimensions (see Sect. 4.1.4). Indeed, we learnt that robots are extensively used as mobile agents for data acquisition and processing (also) thanks to the cities' advanced network technologies, while less efforts are put in improving the cooperative aspects—as demonstrated by the few literature involving intimate-to-

Table 2 Summary of the characteristics for each RCI area

Area <i>Dim.</i>	Urban security	Citizen assistance	Public space engagement	Mobility in Urban dynamic environments	Autonomous Urban transportation	Urban maintainance
<i>Robot type</i>	Highly mobile	Humanoid	Wheeled, Humanoid	Wheeled, Aerial, Marine	Wheeled	Wheeled
<i>Robot actions</i>	Perception, Navigation, Management	Perception, Navigation, Verbal Communication	Perception, Navigation, Verbal Communication	Perception, Navigation, Management	Perception, Navigation, Acquisition	Perception, Navigation
<i>Autonomy level</i>	Medium to High	Medium	Low	Medium to High	High	High
<i>City actuators</i>	Government, Citizen	Government, Citizen	Government, Citizen	Land, Government	Land	Land
<i>City domains</i>	Government, Living	People, Living	Economy, People, Governance	Mobility, People	Mobility, Environment	Governance, Environment
<i>Data volume</i>	MB, GB	MB, GB	MB, GB	MB, GB	MB, GB	MB, GB
<i>Data velocity</i>	Batch/periodic	Batch/real-time	Batch/real-time	Real-time	Real-time	Real-time
<i>Data variety</i>	Mostly un-/semi-	Un-/semi-/structured	Mostly un-/semi-	Mostly un-/semi-	Few structured	Mostly un-/semi-
<i>Data openness</i>	Mostly restricted	Only restricted	Some open	Some open	Some open	Mostly restricted
<i>Robot-citizens interaction</i>	Personal to public	Personal	Social to public	Social to public	Public to social	Public
<i>Robot-land interaction</i>	Exhibit spaces, Passage spaces	Backstage spaces, Exhibit spaces, Passage spaces	Exhibit spaces, Special spaces	Front spaces	Front spaces	Front spaces
<i>Robot-gov. interaction</i>	High	None	None	Some	None	None
<i>Robot-data interaction</i>	Acquisition, Processing, Dissemination	Acquisition, Processing	Acquisition, Processing	Acquisition, Processing	Acquisition, Processing	Acquisition, Processing
<i>Robot-robot interaction</i>	Homo-Heterogeneous teams	Single teams	Single teams	Mostly single teams	Mostly single teams	Single teams, Homogeneous teams

personal robot–citizens interaction, multi-robots cooperation (both heterogeneous and homogeneous teams), robot–governance interaction, and data sharing/dissemination.

5.2 Main Characteristics of RCI

Here, we aim at answering the following question: *which are the main characteristics and challenges of the Robot–City Interaction, based on our findings?*

First, we saw throughout the analysis how RCI has an **interdisciplinary nature**, due to the number of different disciplines contributing to it. Based on this, we say that:

Robot–City Interaction is a cross-disciplinary field of study, combining cutting-edge methods and technologies from a wide range of areas such as Robotics, Information and Communication Technologies, Artificial Intelligence, Knowledge Representation, Ethics, Security and Privacy, to design and implement systems in which autonomous agents are integrated in complex urban environments.

Second, the analysis helped in better assessing the characteristics of RCI, featuring aspects specific to both modern cities and highly autonomous robots, namely:

- *urban robots* which act autonomously in city contexts, both as data producers and data consumers of the city knowledge;
- *smart infrastructures* that centralize and digitalize the urban knowledge from a number of heterogeneous sources, e.g. such as power, water, transports and, ultimately, autonomous robots;
- *open-ended interactions* between robots and the surrounding environment, where proactivity in decision-making is necessary to deal with an unforeseeable number of situations to be dealt with;
- *assistive services* i.e. robots are deployed by and for the city to improve its own services and, consequently, the quality of life of its citizens.

Third, we could then depict the ideal RCI scenario, where:

- (i) robots are enabled with the main cognitive abilities, e.g. they are able to fully observe (through sensors and feedbacks), reason (through integration, analysis and decision-making) and act (through collaborative data sharing);
- (ii) all the actuators of a city (land, citizens, technologies and governance) are involved, i.e. they should all be playing a role in the scenario and benefit from it;
- (iii) a two-way interaction between robot and the city ecosystem happens, in which robots contribute to the city knowledge as mobile data collectors (through data acquisition), but also benefit from the heterogenous knowledge provided by the city (through data dissemination and sharing).

In this view, the main challenge for RCI is to understand *how robots can interact with these large-scale dynamic environments* in a way that such an interaction respects the three constraints of involving fully autonomous cognitive robots, the whole of the city actuators and a bi-directional data communication. As a consequence, works in RCI should focus on designing, implementing and evaluating methods to enable robots to flexibly act in city contexts, namely through the technological advancement of both robots and infrastructures, and through solutions to exploit the large amount of knowledge available nowadays. Although scenarios like these are yet to be achieved, there is a number of efforts that can be put or are being put towards their realization, that we present in the next section.

5.3 RCI: A Research Landscape

Finally, based on our findings and the characteristics of RCI, *which directions can be undertaken, so to facilitate the design and implementation of systems in which robots and cities can better interact with each other?*

The answer to this question finds its origins in the areas directly contributing to RCI. In the rest of the section, some directions which could shape RCI in the future are presented based on three perspectives: infrastructure and data challenges, aiming at improving the integration of robots in city ecosystems; knowledge-related challenges aiming at improving how robots can reason and get conclusions about their surrounding environment; and ethical and policy challenges aiming at determining new norms and regulations to allow the actual implementation of RCI scenarios.

5.3.1 Smart Infrastructures

A major issue arising from the works analyzed is the difficulty in facing the high dynamism, heterogeneity and scale of modern cities. Factors such as monitoring sensors, subject to deterioration, or the presence of citizens, whose actions are unpredictable, bring uncertainty and contradictions, which are difficult to handle even by the most advanced cognitive robots. Planning in uncertain environments is still a challenge for robotics and, for this reason, few projects have been reported as actually being deployed at large-scale (e.g. cities, buildings, streets); an attempt is currently being held within the European Robotics League, aiming at running a number of “robots in smart city challenges” under the ERL in Smart Cities tournaments.¹⁹ Without a way to allow robots to understand how to interact with the surrounding environment, it is clearly difficult to envision an efficient robot–city interaction.

One way to go is to look at it from an IoT and sensor networks perspective, therefore finding ways to guarantee *robust* and *maintainable* infrastructures for a reliable collection, communication and exchange of data. Sensor technologies currently work in small-scaled environments (smart offices, smart homes) but are often not scalable to the cities, as demonstrated by the little effort put in bringing Ambient Intelligence solutions into RCI scenarios. On the other hand, it is evident that a major challenge is on the difficulty of experimenting with such a large, diverse and physically distributed environment like a city. Issues like deployment, testing and simulation of RCI systems are critical to the development of robust research contributions.

In parallel to this, RCI requires efforts towards rethinking robots not as standalone units, but as part of a larger and complex infrastructure. This means not only improving the platforms’ computational and connectivity capabilities, but also to design and implement methods and approaches for reliable data communication and processing, hence guaranteeing the seamless integration of robots with dynamic

¹⁹ <https://www.sciroc.eu>.

interconnected environments. While this would naturally empower robots with the ability of managing the large amounts of data they produce for and they are provided by the city (the *data quantity* problem), an important aspect that needs to be better investigated is for them to better deal with the variety of information sources (the *data heterogeneity* problem) [20].

This also opens an interesting challenge from an ICT perspective, in terms of the capabilities offered by data infrastructures provided by the cities. Data infrastructures are a crucial element in modern cities, since they provide the adequate support for the interaction of the different city systems, robots included. Within the smart cities initiatives, central data management infrastructures have emerged as innovative solutions to build a common facility to efficiently manage, integrate and re-deliver the heterogeneous data from the urban environment. These “city data hubs” [21] are centralized nodes that control and monitor the heterogeneous information provided by the different city systems (e.g. government services, transport and traffic control, water, health care, energy, waste), and whose aim is to reduce the development costs for the applications relying on such services, as well as enabling intelligent data processing mechanisms (mining, analytics, aggregation, alignment, linking) at the scale of the entire city, in a common data infrastructure.

A robust infrastructure for data communication is the necessary condition for the interaction of robots with city environments, and it would allow them to better model the environment and better plan for goal achievement. In order to do this, such infrastructures require new algorithms to process, compute, secure and privatize the information flow from robots to the city, and new mechanisms that clearly expose how to make sense of the available data. In other words, the Data Science techniques that have been employed so far only in highly restricted scenarios (see the RoboEarth [108] framework), have to be adapted to allow more flexible online data processing and sharing mechanisms. Using data with a high degree of organization, or delegating the computation to the main reasoning engine of the data hubs are solutions which would allow the robots’ workload to be relieved, facilitating their management capabilities, their cooperation and their integration in the city infrastructure. By empowering robots with the ability to mine and exploit knowledge from the data hubs, they would be able to filter, prune and restrict their reasoning, therefore improving the performance in achieving their tasks. At the same time, robots should integrate in the city data hubs the knowledge they collected continuously, so that consistent information about objects, people and activities in the environment is always provided to other agents and uncertainty and knowledge gaps are reduced.

In summary, the first research challenge that we can identify is the need of **integrating robots in smart city infrastructures**, which more specifically requires:

- more robust sensors and network communications to guarantee reliable data exchange;
- increase computation and connectivity capabilities for robots to cope with data volume issues;
- extend and improve the capabilities offered to robots by the city data infrastructures;
- new Data Science solutions to mine and exploit city knowledge and deal with data heterogeneity.

5.3.2 Knowledge-Based Environments for Robots

Assuming the symbolic integration between robots and cities, the second direction to take rather concerns the ability of robots to understand and reason with data available from the city. As seen, the lack of structure in the robots’ knowledge representations makes the compilation and data processing a time and energy-consuming task. In this view, semantic technologies [8] have an interesting role to play as means to structure knowledge.

Successfully applied in scenarios aggregating knowledge from heterogeneous sources, semantic technologies provide support both to the representation, integration and curation of data across sources, as well as to the interaction between data and domain experts, towards what can be defined as multi-domain, browsable and accessible conceptual “knowledge city graphs”.

Semantic technologies have proven to have utility in robotics for high-level planning and understanding, and could be exploited as a layer for knowledge representation and exchange in order to facilitate the integration of mobile agents in the cities [101]. Such technologies could hence represent the key that enable robots to behave both as actuators and contributors of a city knowledge base, to better understand the surrounding environment, to reason upon multiple heterogeneous knowledge sources and to improve the performance of their tasks. More specifically:

- (i) without imposing specific data-model constraints, such technologies can intensively facilitate the robots’ high-level reasoning, but also their interoperability, cooperation, and knowledge sharing;
- (ii) thanks to their standards for representing heterogeneous knowledge, semantic technologies could help in better representing the many types of information required for successfully accomplishing robotics tasks (e.g. exact times, 3D geometric information, kinematic structures and appearance models), whose representation is currently very challenging;

- (iii) in the same way, semantic technologies could also support robots in dealing with the diversity of cognitive abilities and of types of knowledge (hybrid reasoning) that is needed to perform their tasks;
- (iv) their flexibility facilitates the representation dynamic environments subject to unexpected and frequent changes, therefore allowing robots to act with more awareness in uncertain and unfamiliar environments.

A further opportunity developed by knowledge-based data management is the use of external knowledge to improve the achievement of robotic tasks. The last decade has seen a huge amount of domain-specific knowledge being openly published in the form structured data, with the objective of encouraging information sharing, reuse and discovery. With this phenomenon of data deluge, building intelligent systems that are able to explore, integrate, and exploit large amounts of heterogeneous data gathered from a variety of distributed sources has become a priority [20,72,100]. Our survey revealed that there is still a long way to go before the machine-readable and accessible knowledge available for reuse and redistribution is exploited by autonomous agents to their full extent. External knowledge could support robots in improving their tasks: for example, a more robust navigation could be performed by relying on open sources representing the geometry of the environment; object search and recognition could be improved through integrating the domain knowledge available in existing ontologies into the robots' semantic maps; while a better understanding of the environment could be achieved if also relying on domain ontologies, rather than relying only on ad-hoc designed robot knowledge representations.

From an AI perspective, more effort has to be put in representing knowledge which is relevant to robotics. There is an urgent need for designing and developing symbolic representations for robots to be more robust and reliable, and efforts focused on representing more common domain knowledge are required (as opposed to the widely-spread instance-based knowledge representations), as this is highly relevant for robots to achieve their tasks. Methods for the evaluation and validation robot knowledge bases are also required. From the institutional perspective, this also means extending and encouraging open data initiatives, through engaging citizens and data providers towards the integration and acceptance of robots acting in smart city environments.

We can define the second research challenge for RCI as the need of **empowering robots with the ability of reasoning with the knowledge from the city**, addressing problems such as:

- leveraging semantic technologies to increase interoperability between robots and city ecosystems;
- exploiting the large amounts of machine-accessible external (and open) knowledge to improve robot tasks;
- enlarging, extending and refining the representations of domain knowledge that can be relevant to robots (and robotics in general);
- encouraging and exploiting open data initiatives.

5.3.3 Ethical Regulations and Policies

The last point of the previous section also relates to the third direction that we have identified in the RCI landscape—namely, how to regulate a robot–city interaction.

Our survey has revealed that several societal and ethical barriers exist, which prevent robots to be extensively employed in cities (see flying drones mostly being used in secure spaces, or driverless systems only used as driving assistants or pedestrian pods). Research areas such as robot ethics, social science, data security and privacy have therefore the opportunity to investigate which methods would allow robots to be more ethically, socially and legally acceptable. HRI approaches are needed to study how to establish fruitful robot–citizens interactions at an intimate and personal distance. When coming to social and public distances, trust issues are to be addressed, as robots in RCI need to operate in environments with citizens that might not have consented to the interaction with them. Social acceptance of robots by naive users is a key issue, and ethical methodologies are needed to guarantee the safety of non-experts creating dynamisms in the environments where robots act, therefore improving the willingness of citizens to share the urban space with robotics platforms. AI trust and transparency tools to explain the logics of robotic behavior and decision-making are also needed [106]. Clear regulations and policies establishing the transparency of data exchange and communication are needed, in order for robots to be respectful of the fundamental laws and rights. By improving policy contexts and by focusing on the citizens' needs, public entities and local authorities could in fact understand what robotics technologies can be offered in response to their urban needs, therefore facilitating the interaction of robotics technologies with political and institutional components.

The last research challenge for the RCI is to establish more **robot-aware societal regulations**, i.e.:

- increase of the robots' social acceptability;
- transparency tools enabling robots to explain their behavior;
- safety dispositions for the citizens when robots operating nearby;
- data protection policies when communicating and exchanging data.

Based on the discussion above, we can conclude that RCI must combine knowledge-based urban environments with modern data infrastructure technologies and robot-aware regulations.

5.4 Relation of RCI to Other Fields

We acknowledge that Robot–City Interaction stands at the crossing of many fields, from robotics and autonomous and intelligent systems to knowledge and information management. We conclude by presenting how RCI relates and differs to its closely related areas.

Ambient Intelligence Ambient Intelligence is mainly concerned with the application of advanced technologies in private spaces [15]. Although many results from Ambient Intelligence can be inherited by RCI, the latter considers private spaces a part of a larger city system, and highlights therefore how the intelligence of urban structures can contribute to use cases of wider scope, e.g. from buildings to towns [2, 14].

Urban Robotics Urban Robotics has been defined as robotics in the service of cities and citizens [85]. While this is very pertinent to RCI, Urban Robotics research applications focus only on exploiting robots to address societal challenges, while omitting the interaction and infrastructure aspects between robots and cities—namely, how these two components can benefit from each other.

Human–Robot Interaction As opposed to Urban Robotics, the main focus of HRI is the interaction between humans and robots (and the ethical and psychological implications of it). HRI studies the different forms of interaction, depending on factors such as the proximity of the participants or the type of robots engaged. RCI and HRI have commonalities, e.g. a solid body a work in HRI finds application in urban spaces, while the proxemics studies help RCI to assess how robots are perceived and received by citizens. The main difference lies in the fact that RCI studies how city services and the citizens' quality of life can be improved by deploying robots as part of an interconnected digital infrastructure.

Roboethics Roboethics also deals with the interaction between robots and humans, but rather focuses on the the human ethical implications of designer, manufacturers, and users of robots [104]. This area overlaps with RCI in what they both address social and ethical issues of the application of robots to our daily lives. Roboethics however focuses on more bio-ethical issues, while RCI addresses ethical implications from a Urban Policy perspective: in other words, in order for robots to operate in a smart city ecosystem, governance measures have to be undertaken too.

Networked Robotics, Cloud Robotics Networked Robotics focuses on the challenges inherent the physical constraints (limited computing and storage capabilities) onboard groups of robot devices connected via wired or wireless com-

munication [46]. Cloud Robotics was then promoted to enable networked robotics with cloud computing technologies. Cooperating robots are expected to operate intensively in a city environment, hence these areas can certainly contribute to RCI with a number of solutions and protocols using existing networks not only for decision making, but also for fast knowledge and data sharing. However, Networked Robotics and Cloud Robotics are rather focused on the hardware, networks and scalability aspects with respect to RCI.

6 Conclusions

Motivated by the advancements of modern technologies in city systems, here we have presented a first attempt to characterize the field of Robot–City Interaction, its key themes, gaps, guidelines and challenges, and to provide a perspective on how robots can interact in and with complex city environments. In order to do so, we used a literature review methodology that allowed us to identify a set of key dimensions of Robot–City Interactions and a body of works contributing to this emerging area, which we then analyzed and classified according to the defined dimensions. The literature review not only served as a ground field for the RCI, to be used for further reference and extension, but also helped us in the following aspects:

- define RCI as the cross-disciplinary field of study, which combines cutting-edge methods and technologies from a wide range of areas such as Robotics, Information and Communication Technologies, Artificial Intelligence, Knowledge Representation, Ethics, Security and Privacy, to design and implement systems in which autonomous agents are integrated in complex urban systems;
- identify the main characteristics of RCI, namely the infrastructure aspect (robots as part of a digitalised infrastructure managing the city services), the interaction aspect (robots behaving as data producers and data consumers of the city knowledge) and the city service aspect (robots are deployed by and for the city to improve its own services);
- identify the main challenges for RCI, designed with the goal of establishing an interaction between robots and complex environments, where the constraints of involving (1) fully autonomous cognitive robots, (2) the four city actuators and (3) a bi-directional data communication are respected;
- identify the six RCI areas, consisting in Citizen Assistance, Public Space Engagement, Mobility in Urban Dynamic Environments, Autonomous Urban Transportation, Urban Security and Urban Maintenance, and their own characteristics;

- outline a vision for future RCI research, emphasising the need for combining knowledge-based urban environments with modern data infrastructures technologies and robot-aware regulations.

Future work can go in several directions. First, we intend to explore several aspects of the RCI landscape—namely, the use of semantic technologies as a knowledge representation layer and the creation of robot–city scenarios at a reduced-scale. Second, we envision to further refine the RCI framework, by providing more detailed analyses of techniques, technical issues (environments, time and costs), impact and key insights specific to each RCI and to single framework dimensions (e.g. robots autonomy or the robot–government interaction). Finally, we intend to include a temporal aspect in the survey, through analyzing how RCI and the different dimensions evolved in time.

Compliance with Ethical Standards

Conflict of interest The authors declare that they have no conflict of interest.

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Appendix

See Table 3.

Table 3 Overview of the literature analysis

	Year	Robot type	Robot actions	Robot Autonomy	City actuators	City domains	Data volume	Data velocity	Data variety	Data openness	Robot-citizens interaction	Robot-land interaction	Robot-Gov. interaction	Robot-Robot interaction	Robot-Data interaction
Urban Security	Petriu et al. [78]	2002	x	x x x	L	x x	x x	x	x	x	x	x	x	x	x
	Hong et al. [44]	2012	x	x x	L	x x	x x	x	x	x	x	x	x	x	x
	Petsch et al. [79]	2012	x	x x	L	x x	x x	x	x	x	x	x	x	x	x
	Cook et al. [16]	2013	x	x x	M	x x	x x	x	x	x	x	x	x	x	x
	Ermacora et al. [26]	2014	x	x x	L	x x	x x	x	x	x	x	x	x	x	x
	Ermacora et al. [27]	2015	x	x x x	M	x x	x x	x	x	x	x	x	x	x	x
	Wagoner et al. [107]	2015	x x	x x x x	H	x x	x x	x	x	x	x	x	x	x	x
	Ermacora et al. [28]	2016	x	x x	L	x x	x x	x	x	x	x	x	x	x	x
Citizen Assistance	Kubotal et al. [55]	2006	x	x x	M	x x	x x	x	x	x	x	x	x	x	x
	Matsumoto et al. [69]	2012	x	x x	M	x x	x x	x	x	x	x	x	x	x	x
	Röning et al. [83]	2014	x	x x	M	x x	x x	x	x	x	x	x	x	x	x
	Tsuji et al. [103]	2015	x	x x	M	x x	x x	x	x	x	x	x	x	x	x
	Bonaccorsi et al. [10]	2016	x	x x	M	x x	x x	x	x	x	x	x	x	x	x
	Hawes et al. [39]	2016	x	x x	M	x x	x x	x	x	x	x	x	x	x	x
	Hoshino et al. [45]	2016	x	x x	M	x x	x x	x	x	x	x	x	x	x	x
Public space Engagement	Datta et al. [22]	2010	x	x x	L	x x	x x	x	x	x	x	x	x	x	x
	Weiss et al. [109]	2010	x	x	L	x x	x x	x	x	x	x	x	x	x	x
	Matson et al. [68]	2011	x	x x	L	x x	x x	x	x	x	x	x	x	x	x
	Shiomi et al. [94]	2011	x	x	L	x x	x x	x	x	x	x	x	x	x	x
	Carton et al. [13]	2013	x	x x	L	x x	x x	x	x	x	x	x	x	x	x
	Sarabia et al. [87]	2013	x	x x	L	x x	x x	x	x	x	x	x	x	x	x
	Kim et al. [53]	2014	x	x x	L	x x	x x	x	x	x	x	x	x	x	x
	Glas et al. [33]	2015	x	x x	L	x x	x x	x	x	x	x	x	x	x	x
	Satake et al. [88]	2015	x	x x	M	x x	x x	x	x	x	x	x	x	x	x
	Foster et al. [30]	2016	x	x x	M	x x	x x	x	x	x	x	x	x	x	x
Mobility in Urban Dynamic Environments	Burgard et al. [11]	1998	x	x x	M	x x	x x	x	x	x	x	x	x	x	x
	Thrun et al. [99]	1999	x	x x	M	x x	x x	x	x	x	x	x	x	x	x
	Siegwart et al. [95]	2003	x	x x	M	x x	x x	x	x	x	x	x	x	x	x
	Lidoris et al. [64]	2007	x	x x	H	x x	x x	x	x	x	x	x	x	x	x
	Althoff et al. [1]	2010	x	x x	M	x x	x x	x	x	x	x	x	x	x	x
	Maier et al. [65]	2010	x	x x	H	x x	x x	x	x	x	x	x	x	x	x
	De Nijs et al. [23]	2011	x	x x	L	x x	x x	x	x	x	x	x	x	x	x
	Lichtenthaeler et al. [63]	2013	x	x	L	x x	x x	x	x	x	x	x	x	x	x
	Kümmerle et al. [56]	2013	x	x	M	x x	x x	x	x	x	x	x	x	x	x
	Trautman et al. [102]	2013	x	x x	L	x x	x x	x	x	x	x	x	x	x	x
	Berkvens et al. [7]	2014	x	x x	H	x x	x x	x	x	x	x	x	x	x	x
	Radwan et al. [80]	2016	x	x x	H	x x	x x	x	x	x	x	x	x	x	x
	Kümmerle et al. [57]	2015	x	x	M	x x	x x	x	x	x	x	x	x	x	x
	Fassbender et al. [29]	2016	x	x x	H	x x	x x	x	x	x	x	x	x	x	x
Autonomous Urban Transportation	Mehhta et al. [70]	2016	x	x x	H	x x	x x	x	x	x	x	x	x	x	x
	Park et al. [77]	2016	x	x x	L	x x	x x	x	x	x	x	x	x	x	x
	Baber et al. [3]	2005	x	x x	H	x x	x x	x	x	x	x	x	x	x	x
	Dresner et al. [25]	2007	x	x x	M	x x	x x	x	x	x	x	x	x	x	x
	Yamauchi et al. [113]	2010	x	x x	L	x x	x x	x	x	x	x	x	x	x	x
	Hashim et al. [38]	2012	x	x x	M	x x	x x	x	x	x	x	x	x	x	x
	Lawitzky et al. [61]	2013	x	x x	H	x x	x x	x	x	x	x	x	x	x	x
	He et al. [40]	2016	x	x x x	H	x x	x x	x	x	x	x	x	x	x	x
	Lee et al. [62]	2016	x	x x	H	x x	x x	x	x	x	x	x	x	x	x
	Khan et al. [51]	2016	x	x x	H	x x	x x	x	x	x	x	x	x	x	x
Urban Maintenance	Schneemann et al. [90]	2016	x	x x	H	x x	x x	x	x	x	x	x	x	x	x
	Wellhausen et al. [110]	2016	x	x x	H	x x	x x	x	x	x	x	x	x	x	x
	Wulfmeier et al. [112]	2016	x	x x	H	x x	x x	x	x	x	x	x	x	x	x
	Hertzberg et al. [42]	1996	x	x x	M	x x	x x	x	x	x	x	x	x	x	x
	Jiang et al. [48]	2005	x	x x	M	x x	x x	x	x	x	x	x	x	x	x
	Nassiraei et al. [75]	2007	x	x x	H	x x	x x	x	x	x	x	x	x	x	x
	Schmidt et al. [89]	2010	x	x x x x	L	x x	x x	x	x	x	x	x	x	x	x
	Helm et al. [41]	2012	x	x x	H	x x	x x	x	x	x	x	x	x	x	x
	Mathibela et al. [67]	2013	x	x x	M	x x	x x	x	x	x	x	x	x	x	x
	Cui et al. [17]	2014	x	x x	M	x x	x x	x	x	x	x	x	x	x	x
	La et al. [59]	2014	x	x x	M	x x	x x	x	x	x	x	x	x	x	x
Latscha et al. [60]	2014	x x	x x x	H	x x	x x	x	x	x	x	x	x	x	x	
Omari et al. [76]	2014	x	x x	H	x x	x x	x	x	x	x	x	x	x	x	
Bartlett et al. [5]	2016	x	x x	H	x x	x x	x	x	x	x	x	x	x	x	
Rahman et al. [81]	2016	x	x x x	H	x x	x x	x	x	x	x	x	x	x	x	
Sandy et al. [86]	2016	x	x x x x	L	x x	x x	x	x	x	x	x	x	x	x	

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