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SURVEY

A Survey on Adaptive Smart Urban Systems

JOÃO CARLOS N. BITTENCOURT [1,2], (Member, IEEE), DANIEL G. COSTA [3], (Senior Member, IEEE), PAULO PORTUGAL [3], (Member, IEEE), AND FRANCISCO VASQUES [4]

[1]CETEC, Federal University of Recôncavo da Bahia, Cruz das Almas 44380-000, Brazil
[2]PDEEC, Faculty of Engineering, University of Porto, 4200-465 Porto, Portugal
[3]SYSTEC-ARISE, Faculty of Engineering, University of Porto, 4200-465 Porto, Portugal
[4]INEGI, Faculty of Engineering, University of Porto, 4200-465 Porto, Portugal

Corresponding author: João Carlos N. Bittencourt (joaocarlos@ufrb.edu.br)

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ABSTRACT The urbanisation of the last century has created a significant demand for urban areas to deliver public services that are efficient, sustainable, and adaptable. This demand is further amplified by the anticipated impacts of climate change and the complexities introduced by rapidly expanding urban populations. In this scenario, smart city initiatives have emerged as a pivotal strategy to address these challenges, leveraging innovative technologies and paradigms such as Internet of Things, Artificial Intelligence, and Data Science to improve the quality of urban life in a more sustainable way. Recently, research efforts in these domains have focused on creating systems that can adapt and respond to changing conditions, enabling greater adaptivity and responsiveness to the needs of urban landscapes. Therefore, this article provides a comprehensive survey of adaptive urban services within a smart city context. Through analyses of recent literature, we investigate the technological foundations that enable the adaptivity of urban services and explore their applications in various urban scenarios, including energy, mobility, emergency management, public safety, and waste management. This article also highlights the benefits of adopting adaptive urban services, such as improved traffic management, resilient emergency management, and enhanced citizen engagement, bringing an important contribution to this broad research area. Finally, we provide a discussion on current technology enablers and challenges and present an overview for future research directions on adaptive urban systems at the forefront of transforming cities into more intelligent ecosystems.

INDEX TERMS Smart cities, Internet of Things, artificial intelligence, data science, adaptivity.

I. INTRODUCTION

The concept of smart cities has rapidly evolved from a futuristic vision to a central strategy for urban development. By leveraging multiple technologies, these disruptive cities aim to enhance the quality of life, operational efficiency, and competitiveness while meeting the economic, social, and environmental needs of present and future generations [1], [2]. At the core of this transformation are smart urban services – technology-enabled solutions designed to manage and improve basic urban services and infrastructure [3]. Although promising, the variability of such smart services pushes us to better comprehend their main advantages and drawbacks when pursuing more sustainable and efficient urban spaces.

In recent years, the development of new technological resources has been crucial in the evolution of smart cities, transforming urban areas into more dependable, efficient,

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and intelligent ecosystems [4], [5]. Cornerstone technological paradigms such as the Internet of Things (IoT), Artificial Intelligence (AI), Data Science, Big Data analytics, and cloud and edge computing underpin a current development trend toward smart urban services [6]. Overall, these technologies equip cities with the means to monitor and manage urban services more effectively, anticipate future needs, and respond proactively to eventual failures and inconsistencies.

As urban populations grow, conventional "static" services are becoming increasingly restricted, even when smart city solutions are considered. Therefore, there is a need for adaptive solutions that can meet the changing needs of urban environments, with "adaptive" referring to the ability to dynamically adjust to new temporal, spatial, and/or environmental urban settings. Since dynamic systems improve the efficiency of urban services by adjusting operations based on real-time data [7], they may lead to more efficient resource utilisation, reduced operational costs, and improved service delivery. However, the implementation of adaptive urban systems is not straightforward since they require continuous adaptation to changes and disruptions in urban scenarios, usually respecting short deadlines and within well-defined hardware and network constraints [8].

Smart urban systems may collect and analyse data from IoT sensors and devices throughout an urban landscape [9]. The ability to process these data in real-time allows for the identification of problems and opportunities, enabling rapid responses to dynamic urban conditions. Beyond this general approach, adaptive systems will typically leverage vast amounts of data to optimise city operations [8], regardless of their sources. As a result, such systems can provide tailored solutions based on data-driven decision-making processes, focusing on seamless configuration and the ability to learn and evolve in response to new contexts. In order to ensure that, the following characteristics are usually sought in adaptive smart urban systems:

- Self-configuration and self-healing: Adaptive systems are expected to be designed to automatically configure themselves based on predefined rules and learned patterns, reducing the need for manual intervention.
- Flexibility: These urban systems must be designed to allow for easy integration of new technologies and sensing capabilities as the city evolves or new requirements emerge.
- Interoperability: The ability to seamlessly integrate and operate across multiple platforms and devices is a distinguishing feature of adaptive urban systems, enabling effective communication and collaboration with other services.
- Predictive analytics: By using advanced analytics and machine learning algorithms, adaptive urban systems can proactively predict future trends and potential problems based on historical and current data.
- Context-aware: Through a localised understanding of the environment, these systems can customise services to meet specific requirements.

It should be noted that not every adaptive system must fulfil all of these characteristics, but this list is crucial to understanding how they differ from traditional solutions. Actually, these elements have been present in recent proposals in multiple ways, giving important clues about the current scenario in this area. For example, adaptive traffic management systems can reduce travel times and fuel consumption by learning and adapting to transit flow [10]. Similarly, adaptive lighting systems decrease energy usage while improving public safety [11]. Moreover, waste management services can optimise garbage collection to conserve resources [12], while adaptive mobility systems adjust to real-time demand to improve efficiency and passenger satisfaction [13]. Actually, these services are just a glimpse of the potential of adaptive urban systems when promoting smart cities.

This article aims to review the application of new technologies and paradigms in enhancing the adaptivity of smart urban services and to identify the benefits and challenges of their implementation, highlighting the importance of adaptive systems for the sustainable development of smart cities. To the best of our knowledge, this article is the first comprehensive review that specifically focuses on exploring adaptive applications within smart city services. In fact, recent survey works have reviewed existing smart urban services, trying to identify their evolution patterns, but adaptive urban services have been transversal in their discussion. For example, the authors of [14] mostly examined smart cities from a multi-system perspective, while the work in [8] highlighted the importance of understanding urbanisation trends and their implications for sustainable urban development. Similarly, the systematic review conducted in [15] addressed the significance of active context-aware systems in developing future smart city applications. As another prominent example, authors of [16] covered spatiotemporal characteristics of sensor data and the importance of interoperability of urban information.

Furthermore, a study conducted in [17] examines the challenges associated with the development of adaptive systems for smart city applications, identifying applications and adaptation aspects. Finally, the authors of [18] explore the challenges of understanding how resilience spreads across urban systems over time, emphasising the necessity for cities to adjust to rapid changes. Nevertheless, unlike previous survey works, this article distinguishes itself by cataloguing and synthesising a wide range of recent studies and presenting recent technological advances in implementing adaptive systems in key urban service domains, including mobility, energy, public safety, and waste management. Particularly, we identify current and future challenges in the field that have not been extensively discussed before, filling a crucial research gap. Furthermore, the literature review introduces a novel perspective on such urban systems by integrating predictive analytics with context-aware technologies, thereby contributing to a holistic approach to urban management.

In order to accomplish our expected goals in this survey, the following three research questions were defined:

- RQ1 – What are the key state-of-the-art adaptive urban systems applications supported by smart cities' infrastructures?
- RQ2 – How do different urban systems incorporate adaptivity?
- RQ3 – Which technological innovations and infrastructural adaptations are essential for adaptive smart urban systems development?

Therefore, the conducted literature review is intended to extract, organise, and discuss fundamental characteristics of adaptive urban services and supporting technologies, enabling us to properly answer these questions. By carefully evaluating the aforementioned research questions, this article contributes to a detailed examination and synthesis of adaptive technologies within smart urban services. The conducted survey categorises and analyses key applications in energy management, mobility, public safety, emergency management, and solid waste management. It also identifies the technological and infrastructural innovations which are essential for developing adaptive smart urban systems. Finally, this article also highlights the research gaps serving as a starting point for future research efforts, suggesting potential directions that could lead to significant advances in the development and implementation of adaptive smart urban services.

The remainder of the article is organised as follows. Section II introduces the fundamental attributes of adaptive urban services. Section III presents a survey of recent applications towards the identification of enabling technologies within urban services, focusing on answering RQ1 and RQ2. Section IV examines the technological foundation that leads to these adaptive urban applications. The article concludes by answering the RQ3 in Section V with a further discussion, which summarises the open challenges and future research directions.

II. FUNDAMENTALS AND BACKGROUND

Smart cities are constantly evolving to integrate innovative control, information, and communication technologies, aiming to better manage urban resources when promoting dependability and sustainability [19]. In this context, the most promising future vision of the smart city concept emerges from the fact that a city is a complex "system of systems" with numerous participants and actors operating in an uncertain environment [14], [20]. Therefore, smart urban systems should be treated as complex adaptive entities that self-organise and evolve in multiple ways, continuously gaining new services-oriented knowledge [21].

Aligned with the evolution of the smart city concept, the development of adaptive smart urban systems involves different formalisms and methodologies. It is then essential to have a comprehensive understanding of the fundamental concepts that underlie this emerging field of study. This section examines such concepts, which were carefully considered according to the performed literature review to ensure that the findings were relevant and impactful. As such, we highlight the key attributes of adaptive urban services, providing a framework for interpreting the development and potential of these applications.

A. SMART URBAN SERVICES

The emergence of smart cities presents a new concept of urban life in which the integration of technology and urban services plays a central role in improving the quality of life for citizens. Smart urban services are at the heart of this transformation, harnessing advanced technologies to create more efficient, sustainable, and liveable urban environments [1], [22]. In fact, these services are not just technological showcases but are expected to be deeply integrated into the daily lives of urban residents, directly contributing to their convenience, safety, and accessibility.

Urban services cover an extensive domain, including healthcare and public safety, as well as the development and management of transportation networks and energy systems [11], [23], [24]. Additionally, the pursuit for sustainability includes ecological preservation, the enrichment of green spaces and proactive environmental protection efforts [25]. Meanwhile, smart cities strengthen security and safety by deploying intelligent surveillance systems and robust emergency response frameworks [26], [27]. These examples illustrate the multifaceted nature of urban services in smart cities, emphasising their crucial role in shaping the future of urban living and governance. By utilising these diverse applications, smart cities can engage in evidence-based planning, informed decision-making, and transparent governance, setting new standards for urban development.

Smart services utilise data and connectivity to perform some urban functionality, tackling some of the most significant challenges that urban areas face nowadays [28]. For example, intelligent transportation systems optimise traffic flow and public transport schedules [10], thus reducing commute times and pollution levels. These services directly benefit citizens by offering more sustainable travel options. Smart energy [29] and waste management systems [30] also contribute to sustainability efforts by efficiently distributing energy based on real-time demand and employing sensor-equipped bins and data-driven collection routes. Consequently, citizens benefit from uninterrupted access to electricity and improved urban cleanliness and public health.

In recent years, the integration of new technologies such as Machine Learning (ML) and Geographic Information Systems (GIS), coupled with the proliferation of data collected by electronic sensors and contributed by government agencies, private sector initiatives and the academic research community, has driven urban services into a new era of responsiveness and contextual awareness [31]. This synergy of technology and information is reshaping the landscape of urban management and leading to an era of adaptive services, in which cities respond to the needs of their residents, dynamically adapting services to the complexities of urban life. In doing so, these urban services are becoming equipped to anticipate and respond to city residents' diverse and ever-changing demands.

B. THE URBAN ADAPTIVE PARADIGM

Urban landscapes are similar to living organisms, constantly evolving and adapting to meet the needs of their inhabitants. This perpetual state of change, driven by demographic shifts, technological advances, and environmental pressures, has highlighted the need for a dynamic approach to urban planning and management [8]. As discussed, urban services can assist in tackling current urban challenges and preparing for future changes, making cities more resilient, efficient, and conducive to a higher quality of life [21]. But by going beyond that and embracing the dynamic nature of the urban environment, smart cities can become truly responsive entities capable of evolving with their landscapes.

Adaptive urban services are essentially characterised by their ability to respond and adapt to continuous change and disruption within a smart city [8], encompassing concurrent systems, resources, and citizens as well. This concept should not be confused with dynamic systems, which focus on understanding the dynamic problems of smart cities and handling them within a System of Systems (SoS) perspective [14]. The key difference lies in the fact that adaptive systems not only understand the dynamic nature of cities but also can actively adapt to them. In contrast, dynamic systems may focus primarily on understanding the dynamics without necessarily having the built-in ability to adjust their operation.

In the context of adaptive systems, the term "adaptivity" is used to describe the system's ability to autonomously adjust its operations in response to changing conditions without human intervention [32]. An example of this is an adaptive traffic management system, which is able to modify traffic light sequences based on traffic flow data. Additionally, the term "adaptability" is used to describe the capacity of a system to be adjusted to meet specific needs. This could be illustrated by a flood detection system that can be adjusted according to weather forecasting [33]. These principles inform the development of adaptive urban systems, ensuring that they can respond to environmental changes and citizens' needs.

To better delineate our focus, this study examines the questions of "when to adapt" [32], "what to adapt", and "according to what to adapt" [33], by providing a comprehensive framework for understanding adaptivity and adaptability within smart urban systems as follows:

- **When to adapt:** Adaptation should occur in response to significant changes in the urban environment, such as traffic congestion, energy demand fluctuations, or critical events. These triggers are identified through continuous monitoring and data analysis, enabling adjustments to the system's operation.
- **What to adapt:** The components of the system that require adaptation include algorithms, configurations, and operational parameters. For example, energy management systems can adjust power distribution based on real-time consumption data.
- **According to what to adapt:** Adaptation decisions are based on a range of contextual factors, including environmental conditions, user behaviour, and system performance metrics.

In general, the architecture of urban services is conceptualised as a multi-layered framework consisting of several key components that work together to deliver efficient services [1]. However, to ensure that urban services are adaptable, scalable, and capable of evolving in response to real-time data, that architecture must encapsulate the essential elements that enable urban services to dynamically adjust to the changing needs of the urban environment and its inhabitants. After a detailed analysis of the literature, we could design a reference architecture that combines previous contributions, as depicted in Figure 1. This architecture integrates advanced technologies and data-driven decision-making processes consisting of four stages: sensing, storage, data management (processing and analytics), and service management (actionable insights). Wrapping all stages provides a continuous feedback mechanism that allows for the constant refinement and evolution of urban services.

Concerning Figure 1, a typical process flow will start with adaptive sensing. Sensor nodes are usually deployed throughout a city to collect data streams on urban dynamics, such as traffic flow, environmental parameters, or utility usage. These sensors are designed to be flexible and adapt their monitoring procedures to the current needs of the target city. In fact, these sensor nodes exemplify the essence of modularity and adaptability by serving as multifunctional units that can be configured to meet the city's shifting demands [16]. The adaptivity of these nodes is further underscored by their ability to receive updates, enabling them to incorporate new algorithms or parameters without necessitating physical intervention [34], [35]. This flexibility ensures that the employed network of sensors remains agile and responsive, aligning seamlessly with urban developments and policy changes.

The data collected are then transmitted to a secure data storage system for further processing. At this stage, raw sensor data are aggregated and may undergo initial filtering to remove noise and irrelevant information or data cleaning to correct errors or fill gaps [36]. Additionally, data reduction techniques are applied to distil the data into a more manageable size while preserving its essential characteristics, ensuring efficient and effective processing in the next step [37]. This pre-processing is essential for refining the data, setting the stage for sophisticated analytics and the derivation of meaningful interpretations that will inform smart city services. Adaptive systems may also leverage spatial and temporal data to aid in providing context-aware data analytics [38].

After being stored, the data are processed using various computational techniques to transform them into meaningful information. These processes include data analytics, pattern

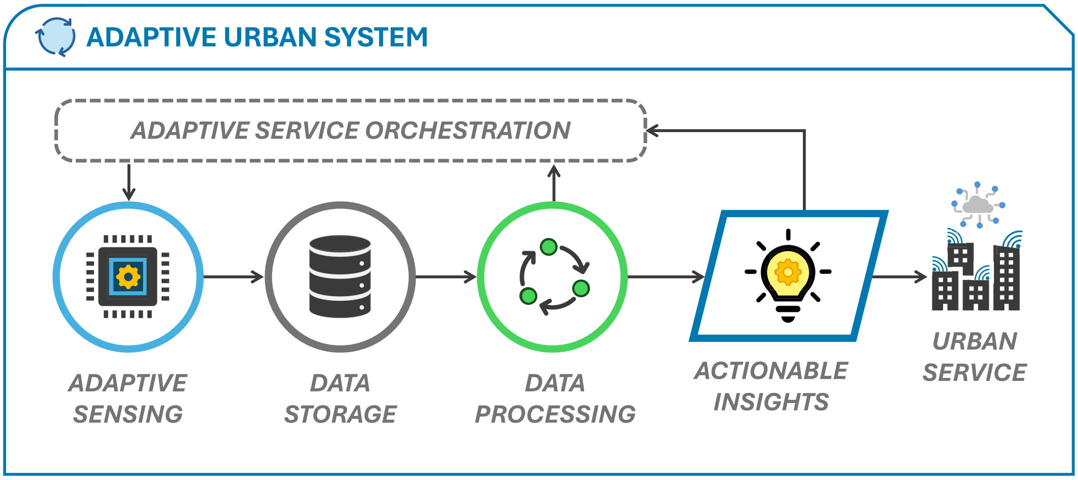

FIGURE 1. The end-to-end process for the paradigm of adaptive urban system.

recognition, and machine learning algorithms that interpret the data. In fact, extracting valuable knowledge from urban data is crucial for many real-world applications. However, the diversity of application scenarios and data types leads to different data analysis tasks and thus requires different learning models [38]. For example, Convolutional Neural Network (CNN) is designed to process image-like data [39], while Recurrent Neural Network (RNN) is typically used to process sequential data [40], [41]. Meanwhile, clustering techniques can be used to identify standard distribution among events in different application domains [42], [43], [44].

The anticipated result is the processing and analysis of data to produce actionable insights. These insights inform decision-making processes, such as adjusting traffic signal timings [45], allocating city resources [29], or issuing public alerts [46]. They are intended to be actionable, meaning they can directly influence the operation of urban services. These insights allow city officials to move beyond static, one-size-fits-all solutions towards more flexible, data-driven strategies that reflect the actual conditions and needs of the urban environment. Additionally, these insights improve predictive decision-making. By examining real-time and historical data, city planners can forecast future trends and patterns, such as predicting peak waste generation times [47] or identifying potential crime risk hotspots [41]. This predictive capability enables city managers to allocate resources, schedule maintenance, and implement preventative measures before issues escalate proactively.

Finally, the retrieved and processed insights are useful for adjusting urban services through dynamic service orchestration. This procedure may involve modifying the intensity or distribution of street lighting based on pedestrian traffic, adjusting waste collection routes in response to fill-level data from smart bins, and altering public transport schedules to accommodate varying passenger numbers, among other responsive services. This process aims to create an urban service ecosystem that dynamically adapts to the real-time conditions and demands of a city, thereby improving overall service delivery and sustainability. Therefore, in order to achieve such adaptability, it is crucial to gain an understanding of the supporting technologies and paradigms.

C. SUPPORTING TECHNOLOGIES AND PARADIGMS

As technology integration has redefined urban liveability, the specific methodologies, frameworks, and innovations behind these services are critical to transforming cities into responsive, adaptive ecosystems. Smart services rely on a technological backbone that spans the Internet of Things, Artificial Intelligence, and Big Data analytics to the cloud and edge computing [9]. The integration of these technologies has been adopted in the literature, leading to the novel concept of adaptive services that are not only reactive to current urban demands but also predictive and adjustable. This section presents a comprehensive overview of some of the most impacting technological advances and driving mechanisms that have empowered adaptive urban services.

1) ELECTRONIC SENSORS AND WIRELESS NETWORKS

The evolution of sensor network infrastructures marks a transformative journey towards the realisation of smart cities. Initially, sensor networks were primarily deployed for specific, isolated tasks, ranging from environmental monitoring to basic urban operations [48]. These networks comprised simple, often uni-functional sensors that collected data passively. However, as the technological landscape advanced, these rudimentary systems evolved into the intelligent sensing ecosystems we see today [49]. This transformation was driven by the integration of advanced computing capabilities, real-time data analytics, and machine-to-machine communications into sensor nodes, enabling them to not only gather data but also interpret and act upon it autonomously.

Wireless Sensor Network (WSN) infrastructures represent a complex mesh of interconnected devices that communicate over wireless networks, offering unprecedented levels of control and automation across various domains of smart cities [1]. In general, WSNs in urban systems harness historical and real-time data to make the city more efficient, sustainable, and reliable [2], [9]. This evolution from simple sensor networks to intricate multi-purpose infrastructures and IoT underscores a pivotal shift towards leveraging digital intelligence to address the multifaceted challenges of urbanisation.

The foundation of smart city operations consists of a vast sensor infrastructure designed to monitor, collect and analyse environmental and urban data in real-time [5]. These sensor units – commonly known as sensor nodes – are equipped with essential monitor, communication, and computation capabilities, thus serving as the "eyes and ears" of a smart city by providing granular insights into its environment. This complex infrastructure is pivotal for data collection and comprises the initial data interpretation and decision-making stages in urban settings [16]. The sensors' capabilities also facilitate scalable and adaptable monitoring networks that can adjust to the changing needs of the urban environment as needed. For example, a sensor node can monitor traffic flow by calculating the average vehicle speed and density over intervals. If these measurements exceed predefined thresholds, it indicates a potential congestion [50]. In an adaptive setting, the node can then immediately adapt its operation to the current scenario by adjusting the signal timing accordingly. This real-time, targeted insight is essential for taking action in urban scenarios.

A sensor node must reliably and accurately monitor and process urban elements. Therefore, to ensure the accuracy and relevance of the collected data, sensors are placed as close as possible to the target monitored area. Local processing can include data filtering, aggregation, and preliminary analysis, enabling sensor nodes to detect and respond to changes in real-time [51]. In addition to data collection, sensor nodes can incorporate communication capabilities that allow them to transmit information to a centralised system or network. This capability bridges the gap between local sensing and broader IoT multi-layered ecosystems [52]. Such decentralised data results in the need for advanced data analysis methods that produces valuable information for decision-making.

2) MACHINE LEARNING AND DATA ANALYTICS

The evolution of machine learning has led to a paradigm shift in urban systems, equipping them with the ability to learn from and respond to complex and fluid urban environments. Essentially, machine learning uses computational algorithms to analyse large data sets, identify patterns, and make decisions with minimal human intervention [53]. This capability is crucial for adaptive urban systems that require continuous evolution in response to changing urban patterns.

Machine learning applications are driven by the concept of learning from experience, similar to the human ability to gain expertise [54]. In the context of smart cities, this means using algorithms to predict various urban situations, optimise resource use, and enhance the quality of life by learning from historical and real-time urban data. The fundamental principles of machine learning, such as supervised learning for prediction, unsupervised learning for data segmentation, and reinforcement learning for strategic decision-making, form the foundation upon which adaptive urban systems are built [55]. By integrating these principles, urban systems can react to present conditions and anticipate future developments, ensuring that cities remain dependable.

The core machine learning techniques, such as regression, classification, and clustering, are the key enablers of adaptive urban systems technologies. They usually operate over the knowledge acquired through large data sets to provide efficient decision-making. Regression models are used to predict continuous outcomes, allowing urban systems to forecast variables such as energy demand or traffic patterns [56]. Classification algorithms are used to categorise data into discrete groups, which can be useful in identifying different types of urban activities or incidents [57]. Clustering is an unsupervised learning technique that detects natural groupings in data [58], being useful for segmenting data from urban areas based on usage patterns or demographic characteristics. All these techniques have an important role in the defined scope of adaptive urban services.

Data analytics comes as another step to extracting valuable insights from large urban data sets [31], allowing urban systems to better understand patterns, trends, and causal relationships. For example, techniques such as time-series analysis can reveal how variables within public transport demand change over time, enabling predictive adjustments to schedule and routing [59]. Spatial analytics can be used to identify geographic patterns in urban growth or service needs, which can guide infrastructure development and resource deployment [60]. Furthermore, by moving beyond predictive models, prescriptive analytics enables city systems to anticipate future scenarios and adjust their strategies proactively. For example, if data analysis indicates an imminent spike in utility demand, an adaptive urban system can self-adjust to implement energy-saving measures [61] or reroute transportation services to balance the load [62]. Therefore, by leveraging data analytics, urban systems acquire a powerful resource to enhance adaptivity.

III. ADAPTIVE URBAN SYSTEMS IN SMART CITIES

The realm of adaptive urban systems uncovers innovative solutions through the utilisation of sensors and machine learning to address the complexities of modern urban life. This section discusses how adaptivity has been applied across various urban services to improve efficiency, resilience, and sustainability, adopting a thorough survey methodology. Each analysed service provides a distinct perspective on the integration of technologies and infrastructure adaptations, demonstrating the wide range of opportunities that adaptive systems offer when pursuing smart cities.

A. ADOPTED SURVEY METHODOLOGY

This article provides a comprehensive overview of recent technological advances in the implementation of adaptive systems within key urban service domains. Therefore, it explores state-of-the-art technologies and their applications in enhancing urban services' efficiency, sustainability, and responsiveness to dynamic conditions. By doing so, it addresses the critical need for cities to adapt to rapid changes in urban environments and the growing citizens' expectations.

The primary source of literature for this survey was the Scopus indexing database because of its broad spectrum of scientific and technical research articles and its highly recognised relevance as a primary indexing database [63]. Following a collection of words and Boolean connectors to access the most accurate information, the following descriptors were considered: Dynamic System, Adaptive System, Reactive System, Adaptable System, Adaptive System, with "AND", "OR" and "PRE\n". The literature search focused on studies published between 2019 and 2024 to capture recent developments in adaptive systems for smart cities, reflecting the latest technological innovations and application trends.

The papers selected were published in peer-reviewed journals or conference proceedings and addressed the application of adaptive systems in urban services. Research papers that included empirical data, case studies, or details on the implementation of adaptive systems were selected. Conversely, papers that did not provide sufficient detail on the methodology, technologies or results and those that were not directly related to adaptive urban systems were excluded. The selected papers were then subjected to a review to assess their relevance and quality. Finally, key information was extracted, including the application objectives, employed technologies, main adaptive characteristics, and which components to adapt.

To systematically explore the vast domain of adaptive smart city services, we categorised the literature into the following areas:

- *Energy Management:* Studies focusing on technologies and systems designed to optimise energy use within urban environments.
- *Mobility:* Research on innovations to improve urban transportation systems, including traffic management, public transit, and pedestrian flow.
- *Public Safety:* Articles addressing the deployment of adaptive systems for enhancing safety measures.
- *Emergency Management:* Studies focusing on efficient context-aware monitoring, emergency response, and disaster prevention.
- *Solid Waste Management:* Literature on applying smart technologies to improve waste collection, recycling, and management processes.

This categorisation facilitated a structured literature analysis, allowing the identification of enabling technologies, applications, challenges, and opportunities within each domain.

Conducting such a survey presents significant challenges. The extensive amount of research available across multiple domains made it difficult to thoroughly cover all relevant studies. Additionally, ensuring consistency and quality of data across different applications was challenging due to significant variations in methodologies and data reporting standards. This diversity across studies also impacted the unification of findings into a single coherent framework. Furthermore, the application and impact of adaptive systems vary considerably depending on the specific urban context, which affects the generalisation of findings and applicable recommendations. In light of these challenges, the methodology employed in this study focuses on understanding how technology is enabling the development of adaptive urban systems. This comprehensive examination offers valuable insights for future research and practical implementations.

Overall, our survey methodology explores the nuances of technological innovations, infrastructural adaptations and their applications in smart cities, building on the thematic exploration of recent advances in adaptive urban systems. We discuss the incorporation of adaptivity in urban systems, illustrating the methodologies and approaches employed to ensure cities can respond dynamically to changing conditions and demands. As a result, this study provides a holistic understanding of the role and impact of technology in promoting resilient and truly intelligent urban ecosystems. Furthermore, this comprehensive literature review reveals promising technological breakthroughs that will significantly enhance the capabilities of adaptive systems.

B. SMART ENERGY MANAGEMENT

As city infrastructures grow and evolve, there is a pressing need for energy-efficient solutions that can keep pace with the changing demands of urban life. Within this scenario, intelligent energy management systems are essential to creating sustainable cities. These systems manage and distribute energy resources, reducing the environmental impact of urban areas [64]. Nevertheless, in order to ensure sustainability, the adoption of more adaptive systems is rather fundamental. By anticipating and responding to energy demands and potential disturbances, these systems can improve the overall efficiency of the energy supply infrastructure.

Energy distribution has substantially evolved in recent years, driven by the widespread adoption of different energy sources. In order to highlight the potential of adaptive urban systems, authors in [29] propose an optimisation model for energy reserves in urban environments. The study focuses on a forward-looking approach that anticipates and adapts to the varying demands and supply conditions. Additionally, by exploring effective policies and dynamic management through data-driven approaches, cities can achieve more resilient and citizen-aware energy services [64].

As cities strive to meet their sustainability goals, they are turning to integrating and managing renewable energy sources to ensure a reliable supply chain [65]. By taking advantage of deep reinforcement learning, the authors of [61] leverage an edge and cloud infrastructure to actively update the learning models and improve the efficiency of multi-source energy distribution according to user demand. Aiming to enforce the reliability of renewable energy sources, [66] introduces a data-driven approach that optimises the maintenance of solar photovoltaic systems. The framework establishes a continuous feedback loop where real-time fault detection triggers responses, ensuring efficient anomaly maintenance and system updates. Furthermore, the work in [67] proposed an adaptive system for predicting solar radiation, enabling more accurate forecasts of energy production.

Driven by the development of electric vehicles, the charging infrastructure has become crucial for incorporating them into the energy matrix [68]. Due to varying demand patterns and the natural dynamics of urban areas, this emerging trend underlines the importance of systems that can adapt to this changing scenario. In [69], authors introduce a framework for the charging stations, ensuring that the infrastructure can adapt to the varying demands of connected vehicles. Progressing further into efficiency and sustainability, [70] examines the strategic integration of dynamic wireless charging systems within urban settings. This approach facilitates on-demand energy distribution through the power tracks, emphasising the role of adaptation towards balancing energy demands. Moreover, the technical nuances of optimising wireless charging systems are explored in [71], highlighting the need for learning and adapting to road power parameter variations for maximised efficiency.

Adaptive energy systems are also emphasised by intelligent street lighting services, which aim to improve energy efficiency and public safety. A large body of literature has investigated the efficient management of urban lighting systems, promoting the adoption of systems able to adjust illumination based on environmental conditions and human occupancy [11], [72], [73]. These studies demonstrate the potential for significant energy savings, improved safety, and scalability in urban settings. However, lightning management systems might explore the potential of AI and machine learning algorithms to achieve high efficiency. For example, a fuzzy control mechanism is used in [74] to optimise energy usage in streetlights, emphasising the integration of adaptive algorithms to enhance smart lighting. Additionally, the integration of sensors to enable more responsive solutions is emphasised in [75]. That study utilises adjustable delay sensing and adaptive control agents based on traffic conditions to enhance the efficiency of the system as a whole.

Table 1 presents a summary of the adaptive systems used in smart energy management and their associated adaptation strategies. Furthermore, Figure 2 reveals that context-awareness and predictive analysis are the most prevalent features in adaptive energy systems. These characteristics facilitate adaptation and forecasting future conditions, thereby optimising performance and efficiency. Moreover, self-configuration allows autonomous system adjustments, which is of significant importance in improving reliability

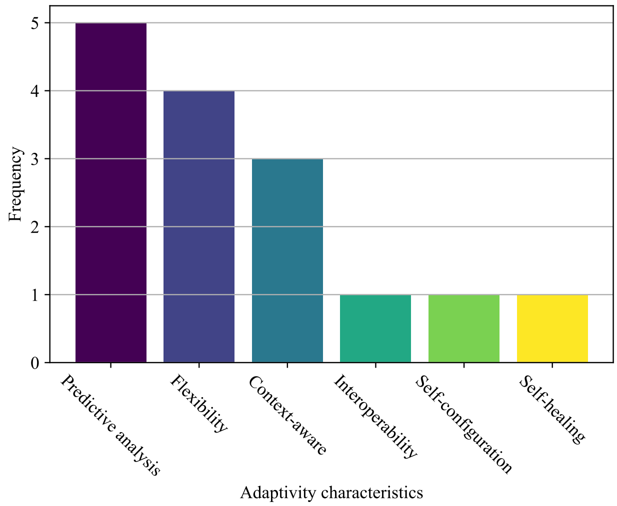

FIGURE 2. Frequency of adaptivity characteristics in smart energy management systems.

and collaborating towards the sustainability of energy distribution. Finally, the analysis also demonstrates that interoperability and self-healing, while crucial for ensuring seamless integration and reliability, are still less frequently explored in the recent literature. The overall applications' perspective highlights the emphasis on real-time data utilization and autonomous decision-making to enhance the resilience and efficiency of smart energy management services.

C. SMART MOBILITY

Adaptive smart mobility marks an innovative era in urban transport services, characterised by rapid technological innovation that fosters more dynamic, effective, and user-centric services. These advancements span various applications, including sophisticated traffic management and comprehensive mobility solutions [76]. Through the strategic integration of technology, these systems not only cater to the immediate requirements of city residents but also possess the foresight to adapt to emerging needs.

A significant part of this progress lies in the development of Adaptive Traffic Signal Control (ATSC) systems, as they are essential for optimising traffic flow and reducing congestion. These systems employ several techniques to adjust signal timing based on real-time traffic conditions. For example, the authors in [77] use WSN to implement an adaptive traffic light synchronisation algorithm in regions composed of several consecutive junctions. This technique improved traffic flow by reducing the start-stop effect. However, such general solutions can easily lead to starvation in main lanes during peak hours. This problem is addressed in [78] by adjusting the traffic lights' priorities according to the current flow. Moreover, the work of [79] demonstrates the potential of CNN for enhancing adaptive congestion controllers by using visual information to adjust their timing parameters.

Real-time traffic data and machine learning optimisation can also significantly reduce delays by adjusting signal

TABLE 1. Adaptive systems in smart energy management.

Work	Application	Technologies	Characteristic	Adaptation strategy
[29]	Energy reserve optimisation	Data analytics	Predictive analysis Context-aware	Adaptive forecast energy reserve dispatch and balancing regulation.
[11]	Adaptive street lighting control	Wireless sensors integration Edge computing	Interoperability Context-aware	Regulate the street light intensity based on traffic presence and integrate lighting poles to increase their amplitude continuously.
[75]	Remote street lighting control	Wireless sensors integration Cloud computing	Flexibility Context-aware	Automatic regulation of lightning control delay sensing based on environment light intensity.
[61]	Scheduling energy distribution	Wireless sensors integration Cloud computing Edge computing Machine learning	Flexibility Self-configuration Predictive analysis	Dynamic energy distribution based on consumption and user demand.
[66]	Fault detection in energy production	Sensor integration Cloud computing Data analytics	Flexibility Self-healing Predictive analysis	Adapting operation to changing environments, while identifying and learning from anomalies that indicate degradation.
[67]	Forecast solar energy generation	Machine learning Geographic Information System	Predictive analysis	Predict energy production in short-term periods based on spatiotemporal geolocated data.
[70]	Electric vehicles wireless charging	Data analytics	Flexibility Predictive analysis	Dynamic scheduling of electrical vehicles wireless charging based on traffic information.

timings preemptively [80]. Such intelligent traffic control systems are evaluated in [81], [82], and [83], leveraging a combination of edge computing and reinforcement learning to adjust signal timings to the actual traffic condition. These ATSC systems demonstrate the potential for significant improvements in urban traffic management by self-configuring parameters according to the urban dynamics. Similarly, the authors of [84] proposed a simulation-based traffic signal control strategy to optimise traffic flow by adjusting signals in response to real-time conditions. This adaptive method demonstrated high efficiency in reducing congestion and improving traffic.

Traffic light management is essential for developing efficient mobility services in large cities. However, there are still a multitude of concerns when it comes to traffic management. The current scenario is boosted by the urgent need to achieve sustainability goals. Hence, reducing congestion, improving safety, and increasing efficiency in the traffic network has gained more attention in the last years [85]. In this context, adaptive systems have demonstrated their ability to leverage traffic infrastructure to provide residents with context-aware and highly efficient mobility systems. This potential is illustrated in [86] through an adaptive model that leverages data collected from connected vehicles to enhance decision-making flexibility, enabling the system to respond to varying circumstances, such as congestion, emergencies, and other dynamic factors influencing traffic flow.

The evolution of vehicle communication infrastructure is closely related to advancements in adaptive urban systems by providing reliable means to collect environmental and road conditions data seamlessly [87]. Focusing on utilising fog computing and vehicle-to-infrastructure networks, authors of [88] detect and classify street pavement anomalies in real-time, exploiting machine learning techniques. This approach enhances decision-making by mapping street quality and identifying significant anomalies, providing a means to address such issues dynamically according to needs. Additionally, ubiquitous cloud resources and smart driving advances improve the potential of car-to-cloud communication [89]. Overall, studies in this field emphasise the role of this technology in supporting the integration of dynamic learning of urban infrastructure information within city services.

Incorporating data collected from electronic sensors and cameras is still paramount in processing traffic information. Such integration allows an adaptive system that predicts travel time based on real-time and historical data, leading to routes with minimal travel time [7], [57]. Furthermore, the data collected from distributed sensors allows the detection of anomalies in the traffic system, such as accidents and congestion [10]. This predictive capability is crucial for preemptive traffic management and to mitigate potential issues before they occur, highlighting the adaptive nature of traffic control systems that learn and evolve. Finally, authors in [90] demonstrate how regression models and spatiotemporal data processing mechanisms can predict traffic conditions by focusing on the importance of modelling complex spatial dependencies and temporal dynamics.

Intelligent parking solutions can also benefit from spatiotemporal data, making the city more responsive and citizen-centric. In [91], the authors present a parking information system that uses sensors and cameras to monitor parking space occupancy, adopting a Petri Net model for dynamic adaptivity to sensor changes and failures, illustrating a proactive approach to efficient management of urban parking spaces. Meanwhile, the work in [92] proposes an agent-oriented smart parking recommendation system that prioritises driver preferences such as parking type, cost, and proximity to destination to achieve an adaptive parking reservation process. This perspective is further extended in [93] using WSN and machine learning to predict parking occupancy using traffic cameras and weather forecasting services. That approach demonstrates the potential of such technologies in predicting and managing availability, reducing the time a driver spends looking for an available parking spot.

From a different perspective of mobility planning, effective public transport systems and carpooling can also achieve higher efficiency through adaptive urban systems. The demands of citizens and the natural dynamic of cities raise the need for dynamic public transportation routing systems. The authors in [62] address this issue by comparing the efficiency of adaptive and static bus routes, emphasising the importance of flexible public transportation services. Similarly, the work in [94] proposes a predictive monitoring framework for bike-sharing systems, employing neural networks to classify and preemptively address service violations. In the context of carpooling, authors in [13] focus on dynamic ride-sourcing, presenting a model that improves vehicle-passenger matching and repositioning to minimise waiting times and optimise network flow. In a different approach, learning through the demand to improve service rates and efficiency without increasing fleet sizes can balance taxi distribution in ride-sharing services, as addressed in [95].

Table 2 summarises the surveyed works that implemented some level of adaptivity by exploiting different technologies. The characteristics of the surveyed adaptive mobility applications are further emphasised in Figure 3, which shows that context-awareness, self-configuration, and predictive analysis are the most common. Context-awareness enables systems to optimise traffic flow and safety by adapting mobility services based on real-time traffic data. This adaptivity has been commonly applied to traffic light systems and efficient traffic re-routing. Furthermore, self-configuration allows for autonomous adjustments to maintain optimal performance in response to variations in urban settings. Finally, predictive analysis facilitates the forecasting of traffic patterns and the enhancement of system reliability. Collectively, the studies underscore the significance of autonomous decision-making based on real-time data in enabling adaptivity in smart mobility applications.

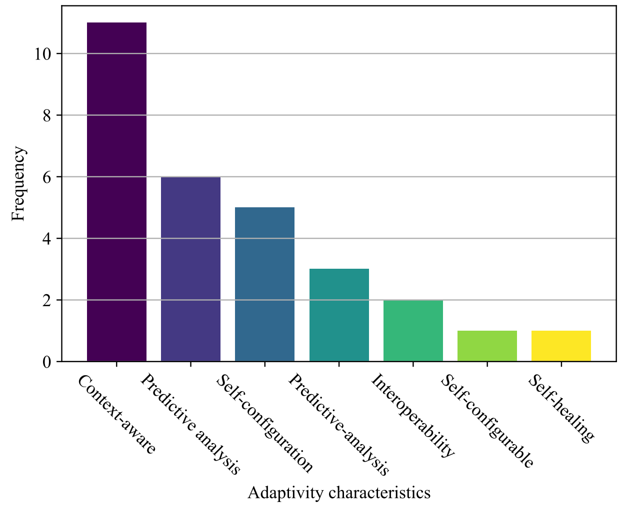

FIGURE 3. Frequency of adaptivity characteristics in adaptive smart mobility systems.

D. SMART EMERGENCY MANAGEMENT

Emergency management systems are a crucial urban service that plays a vital role in protecting urban populations and infrastructure from the impacts of unexpected events and disasters. These systems enable cities to respond quickly and effectively to emergencies, minimising potential damage and disruptions. However, to enhance their reliability and enable adjustments in response to the dynamic nature of emerging threats, it is crucial to incorporate adaptivity into these systems. This capability improves the accuracy of response efforts and ensures that cities can maintain resilience and continuity in the face of diverse and evolving challenges.

Several studies have explored the frontiers of emergency detection and focused on improving the adaptivity of sensor networks in smart cities. The authors in [46] propose a configurable wireless sensor network aimed at precise and energy-efficient urban emergency management. That framework consists of emergency detection units that can play different roles in the emergency management process, from sensor-based to AI-based detection. In a similar way, the work in [96] tackles the challenge of energy efficiency in disaster management systems using WSN by introducing a modified metaheuristic algorithm that incorporates an adjustable sensing range mechanism in order to avoid overlapping coverage.

In an effort to address the complexities of smart city ecosystems, researchers have adopted holistic methodologies for emergency management. Emphasising this need, authors in [97] use a probabilistic model check to represent the dynamics and uncertainties in the emergency services of smart cities. The system captures the varying severity of emergencies and dynamically dispatches the required emergency response units to the event location. Following a similar approach, the authors in [98] focus on the targeted deployment of emergency vehicles based on sensor-generated alarms. The method dispatches the most suitable vehicles based on their location, using the type of alarm. Furthermore, [99] presents a novel terrain-adaptive unmanned ground vehicle designed for underground space emergencies. The vehicle integrates obstacle detection and a terrain-adaptive mechanical module for several search and rescue operations.

TABLE 2. Adaptive systems in smart mobility.

Work	Application	Technologies	Characteristic	Adaptation strategy
[77]	Traffic congestion reduction	Wireless sensors integration	Self-configuration Context-aware	Synchronising traffic lights controlling consecutive junctions by creating a delay dynamically updated based on the number of vehicles waiting.
[78]	Priority-based traffic signals control	Wireless sensors integration Edge computing	Self-configuration Context-aware	Adjust traffic signal timing based on vehicle priorities and road lane pressure.
[79]	Traffic signals management	Wireless sensors integration Machine learning	Self-configurable Context-aware	Adapt the traffic light control based on the traffic flow in junctions.
[82]	Traffic congestion management	Wireless sensors integration Machine learning Data analytics	Predictive analysis Interoperability Context-aware	Adjust traffic signal timings by learning the characteristics of traffic data.
[83]	Road traffic congestion control	Machine learning Data analytics	Predictive-analysis	Analyse traffic congestion and environmental variables to predict traffic congestion.
[81]	Road traffic congestion control	Wireless sensors integration Machine learning Data analytics	Context-aware	Adjust traffic lights in real-time based on vehicle density present at the traffic post.
[86]	Traffic monitoring	Wireless sensor integration Machine learning Data analytics	Interoperability Context-aware	Considers multiple features of the in-range traffic management vehicles providing reliable routing.
[7]	Traffic route management	Wireless sensor integration Data analytics	Predictive analysis Context-aware	Identify minimal travel time path based on streamlined traffic information.
[88]	Road management	Wireless sensor integration Edge/Fog computing	Context-aware	Targeted road anomaly identification
[89]	Mobility infrastructure	Wireless sensor integration Cloud computing	Self-configuration	Adaptive car-to-car communication
[10]	Parking management	Wireless sensor integration	Self-configuration Self-healing	Adjust parking information
[90]	Traffic management	Data analytics Machine learning	Predictive-analysis	Spatiotemporal traffic prediction
[91]	Traffic management	Data analytics Machine learning	Predictive-analysis	Spatiotemporal traffic prediction
[92]	Parking management	Wireless sensor integration Cloud computing	Context-aware	Parking spot reservation
[93]	Parking management	Wireless sensor integration Cloud computing Machine learning	Predictive analysis	Predictive park occupancy
[94]	Bike-sharing management	Wireless sensor integration Machine learning	Predictive analysis Context-aware	Optimise bike-sharing systems
[84]	Simulation-based traffic signal control	Wireless sensor integration Machine learning Data analysis	Predictive analysis Context-awareness Self-configuration	Adjust traffic light parameters based on traffic conditions.
[95]	Carpooling services	Data analytics	Predictive analysis	Balance taxi distribution

During emergency rescue operations, exploring debris along affected buildings remains a significant challenge. To address this issue, the integration of adaptive technologies into Building Information Modelling (BIM) and Structural Health Monitoring (SHM) has emerged as a promising solution for ensuring urban safety [100]. These techniques enable the identification and monitoring of structural health indicators, facilitating the early detection of potential hazards. In fact, dynamic BIM systems can improve the safety and efficiency of public buildings by enabling real-time visualisation and dynamic SHM, as demonstrated in [101]. Complementing these efforts, the authors of [102] highlight the necessity of dynamic emergency evacuation planning in large public buildings. They address the limitations of static evacuation plans with an intelligent building approach to deliver an effective evacuation system under various emergency scenarios.

Life-threatening emergencies require immediate attention. In such situations, every second counts, and prompt medical intervention can make all the difference between life and death. Therefore, the prioritisation of emergency vehicles is crucial, as it ensures that these vehicles reach their destination as quickly as possible. Within this context, the work in [103] presents a framework that dynamically adjusts traffic lights to facilitate the passage of emergency vehicles. This system utilises sensors and a localisation system, alongside machine learning, to prioritise emergency vehicles while adapting traffic light patterns based on vehicle density. Furthermore, intelligent signal scheduling for emergency vehicles using WSN enables ambulances to dynamically control traffic signals based on their location and traffic density [59].

Still considering traffic management during emergencies, [104] proposed an integrated adaptive control system that uses fuzzy logic to ensure emergency vehicle prioritisation while allowing for pedestrian flow. Finally, [105] introduced a software-defined traffic light preemption mechanism that uses vehicle communications and applies an adaptive algorithm for redefining emergency medical services routes based on traffic conditions.

Table 3 summarises the discussed works. In addition, Figure 4 illustrates the pivotal role of context-awareness in enabling systems to adjust based on environmental data, thereby enhancing the effectiveness and responsiveness of emergency responses. Furthermore, self-configuration has demonstrated the potential to autonomously adjust systems' settings in response to changing urban conditions, which is vital for maintaining reliability without manual intervention. Similarly, predictive analytics is crucial to emergency management systems since it enables the forecasting of critical scenarios and preparing accordingly, thus improving response times and decision-making. Finally, although less frequently explored, interoperability has been utilised to provide seamless integration and communication among various emergency management technologies.

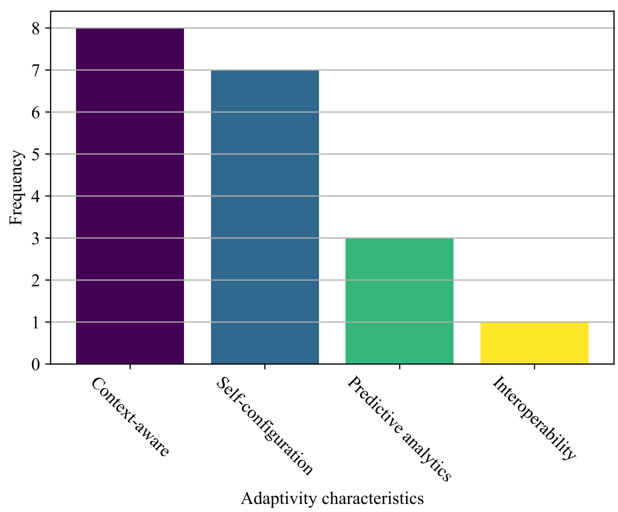

FIGURE 4. Frequency of adaptivity characteristics in adaptive emergency management systems.

E. SMART PUBLIC SECURITY

Integrating advanced technologies into urban security systems is crucial to improve safety in smart cities. Recent research has made important advances in this area, focusing on the development of adaptive systems to create safer and more responsive environments. Although security incidents are inherently urban emergencies, their impact on daily activities makes them a special case that demands proper treatment. This results in a particular group of urban services that can also strongly benefit from the adaptive paradigm.

Through the development of an adaptive, age-invariant facial recognition system, the work in [106] proposes an integrated approach to surveillance in urban environments. That system incorporates CNN into cameras to autonomously update databases and ensure effective detection and identification. Emphasising the need for adaptive decision support models tailored to different contexts of city surveillance highlights the potential of urban technology integration and adaptivity to address crime prevention [107]. This synergy also illustrates the interoperability of spatial-temporal data collected from surveillance systems in the cities' evolution.

Custom surveillance systems are provided by a thorough assessment of spatial features and temporal patterns. The authors in [108] highlight the significance of spatiotemporal data analysis in public safety strategies through a smart city digital twin method that dynamically places license plate reader sensors to optimise public safety. The study of [109] contributes to the field of crime prevention to predict crime locations and simulate suspect vehicle movements. Their method focuses on the application of region-based video surveillance, using deep learning to efficiently adjust and transmit high-quality and lightweight visual data.

Due to the acceleration of urbanisation, the need for efficient urban security mechanisms has increased significantly, particularly in crime prediction efforts. This reflects a shift towards harnessing data-driven insights to ensure the adaptivity and effectiveness of security measures. The study presented in [110] explores crime prediction through the lens of social media, employing a Support Vector Machine (SVM) to analyse extracted features from posts. Their approach allows for the learning and prediction of criminal acts in specific spatial and temporal windows. Concurrently, authors of [41] focus on capturing the spatiotemporal dynamics of crime records. Their solution enables efficient allocation of police resources based on understanding crime dynamics.

TABLE 3. Adaptive systems in smart emergency management.

Work	Application	Technologies	Characteristic	Adaptation strategy
[46]	Distribute emergency detection processing	Wireless sensor integration Artificial Intelligence	Self-configuration Context-aware	Dynamically distribute tasks among a set of heterogeneous sensor units
[96]	Improve sensors' energy efficiency	Wireless sensor integration Artificial Intelligence	Self-configuration	Adjust sensing range based on overlapping coverage
[97]	Severity-based emergency response	Wireless sensor integration Data analytics	Context-aware Predictive analytics	Dynamic dispatch emergency response units according to event severity.
[98]	Emergency-based vehicle dispatch	Wireless sensor integration	Context-aware	Targeted assignment of emergence vehicles according to the hazards.
[99]	Unmanned search and rescue	Sensor integration	Self-configuration Context-aware	Adapt an unmanned vehicle according to the obstacles and terrain.
[101]	Structural health monitoring	Wireless sensor integration Data analytics	Predictive analytics	Early detection of potential hazards based on real-time visualisation.
[102]	Emergency evacuating planning	Wireless sensor integration Data analytics	Context-aware Predictive analytics	Adapt evacuation plans based on current emergency scenario.
[103]	Prioritise emergency vehicles	Wireless sensor integration Machine learning	Self-configuration Context-aware	Dynamically adjust traffic lights to facilitate emergency vehicles passage.
[59]	Remote traffic lights control	Wireless sensor integration	Self-configuration	Control traffic lights signals based on the location of emergency vehicles.
[104]	Multi-purpose traffic light control	Sensor integration Data analytics	Self-configuration Context-aware Interoperability	Optimise traffic light prioritisation for emergency vehicle and pedestrian crossing.
[105]	Preemptive traffic lights control	Wireless sensor integration	Self-configuration Context-aware	Redefining emergency services routes based on traffic real-time conditions.

However, predicting crime across different departments requires sorting through a large amount of information from multiple sources, often characterised by varying degrees of structural inconsistency and unlabelled data [111]. The study in [112] addresses this challenge through unsupervised domain adaptation. They propose to construct auxiliary contexts for target cities based on similar source city grids, thereby resolving inconsistencies in context data between cities while facilitating adaptation and interoperability.

After the performed discussions, Table 4 summarises the surveyed works in this area. As illustrated in Figure 5, predictive analytics represents the most prevalent feature in smart public security systems, thereby underscoring its pivotal role in anticipating and mitigating security risks. Systems that utilise predictive analytics are able to predict criminal activities and adjust their operations accordingly, thereby improving the effectiveness of urban surveillance and crime prevention strategies. Another prominent feature is self-configuration, which ensures optimal performance without the need for manual intervention. For example, urban surveillance systems can autonomously adjust image quality based on specific regions of interest. Finally, context-awareness allows these systems to adapt to the spatial and temporal context of urban environments.

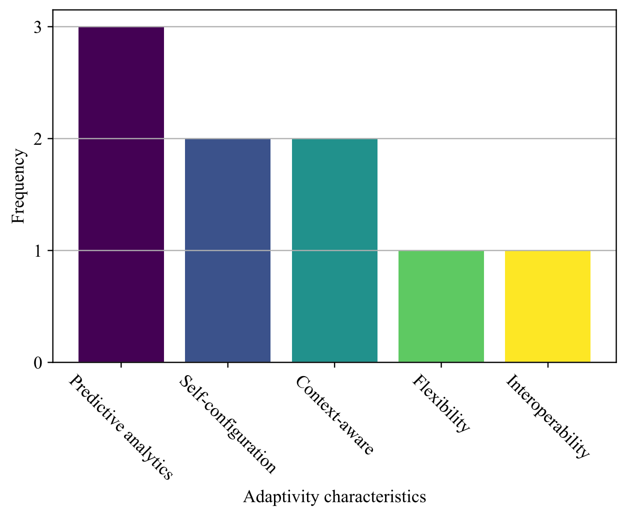

FIGURE 5. Frequency of adaptivity characteristics in adaptive public safety systems.

TABLE 4. Adaptive systems in smart public security.

Work	Application	Technologies	Characteristic	Adaptation strategy
[106]	Urban surveillance	Machine learning Data analytics	Self-configuration Flexibility	Autonomous updates face-recognition databases
[108]	License plate reader sensor positioning	Sensor integration Machine learning Data analytics	Predictive analytics	Spatiotemporal data analysis that dynamically places license plate reader sensors.
[109]	Urban surveillance	Machine learning	Self-configuration	Dynamically adjust the image quality based on specific regions of interest.
[110]	Crime prediction	Machine learning Data analytics	Predictive analytics Context-aware	Predict criminal acts in specific spatial and temporal windows based on learning standards.
[41]	Crime prediction	Machine learning	Predictive analytics	Capture the spatial and temporal dynamics to improve crime forecast analysis.
[112]	Crime prediction	Machine learning	Context-aware Interoperability	Contextualise the information domain of different cities to improve crime prediction.

F. SMART SOLID WASTE MANAGEMENT

As urban populations swell and the quest for sustainable living intensifies, the management of urban waste emerges as a critical challenge demanding innovative solutions [113]. Adaptive technologies in waste management are pivotal in transforming urban systems into smarter, more efficient entities. The integration of machine learning into solid waste management systems and electronic waste (E-Waste) management illustrates the forefront of this transformation [114]. This scenario leads to smart cities leveraging remote sensing technologies and data-driven approaches to support operational adaptivity and environmental sustainability in waste management systems [115].

Recent research on smart bins has shown promising advancements in addressing the increasing complexities and demands of urban waste management. In particular, waste collection optimisation based on predictive modelling and machine learning can help to streamline the collection routes [44], [116]. These methods underscore the necessity of dynamic routing and the significant impact of real-time data on operational efficiencies. Similarly, authors in [117] and [118] investigate smart waste collection through a dynamic multi-compartment vehicle routing problem and a sensor-based intelligent system. Their emphasis on real-time data analytics and energy-efficient route optimisation demonstrate the adaptivity of waste management systems to varying urban conditions and waste generation patterns.

Still considering this trend, the work in [12] highlights the importance of predictive analytics and real-time monitoring in waste management. By leveraging WSN to monitor waste levels and applying cognitive frameworks for route selection, these studies present solutions that improve operational efficiency and contribute to environmental sustainability. Supplementing these studies, [119], [120] assess the economic and environmental benefits of smart bin implementations and propose real-time waste management algorithms that dynamically adjust collection planning.

This current shift towards leveraging real-time data to improve the responsiveness and efficiency of waste management systems has also led to innovative approaches that optimise waste collection planning processes. Authors in [121] propose a dynamic waste collection model that uses smart bin sensors to facilitate real-time waste management and optimise the collection. Similarly, [122] improve unplanned waste collection using sensors for dynamic route planning to efficiently manage occasional waste types.

Finally, [47], [123] explore dynamic data-driven models emphasising route scheduling optimisation for waste collection vehicles. Authors in [123] propose a model considering the socioeconomic characteristics of customers, integrating fill-level sensor data in smart bins toward an efficient collection schedule, whereas the work in [47] introduces a novel cost function that incorporates sensors and real-time road traffic information to optimise routes, demonstrating significant reductions service delays. A summary of the surveyed articles is presented in Table 5.

Figure 6 demonstrates the prevalence of adaptivity characteristics identified in the surveyed works on smart waste management systems. The prevalence of context-aware approaches underscores the importance of adjusting based on data regarding current waste levels, with the objective of enhancing the efficiency of collection routes. Moreover, predictive analysis enables forecasting waste generation patterns and optimising operational strategies. This technique enables the prediction of when bins will be full, thus allowing the self-adjustment of collection schedules. This capability has been demonstrated to have potential applications in smart waste bin management, where the anticipation of future states can significantly enhance system reliability and efficiency.

TABLE 5. Adaptive systems in smart solid waste management.

Work	Application	Technologies	Characteristic	Adaptation strategy
[116]	Waste collection vehicle routing	Wireless sensor integration	Context-aware	Create an optimal waste collection route by using up-to-date data on waste bin levels.
[44]	Waste collection vehicle routing	Wireless sensor integration Machine learning	Context-aware	Define dynamic optimal routes by grouping waste bins into clusters to reduce the subset that a vehicle will visit.
[117]	Waste collection vehicle routing	Wireless sensor integration Data analytics	Context-aware	Define dynamic routes to minimise transportation and penalty costs incurred from exceeding bin capacity.
[118]	Smart waste bin management	Wireless sensor integration Machine learning Cloud computing	Context-aware Predictive analysis	Conserve energy in waste bins, generate missing data values from sensors, and select the optimal routing path for garbage trucks.
[12]	Waste collection vehicle routing	Wireless sensor integration Machine learning Cloud computing	Predictive analytics	Learn and predict the upcoming wastage based on waste generation patterns.
[119]	Smart waste bin management	Wireless sensor integration	Predictive analysis	Make predictions on smart bins residual capacity, considering the changes in terms of frequency of bins collected and dynamic vehicle routing.
[120]	Waste collection vehicle routing	Wireless sensor integration Cloud computing	Context-aware	Prioritise smart bins by detecting when they are significantly full and dynamically rerouting the waste collection vehicle.
[121]	Waste collection scheduling	Wireless sensor integration Cloud computing	Context-aware	Integrating real-time weather, distance traffic, and smart bins sensor data to improve the collection.

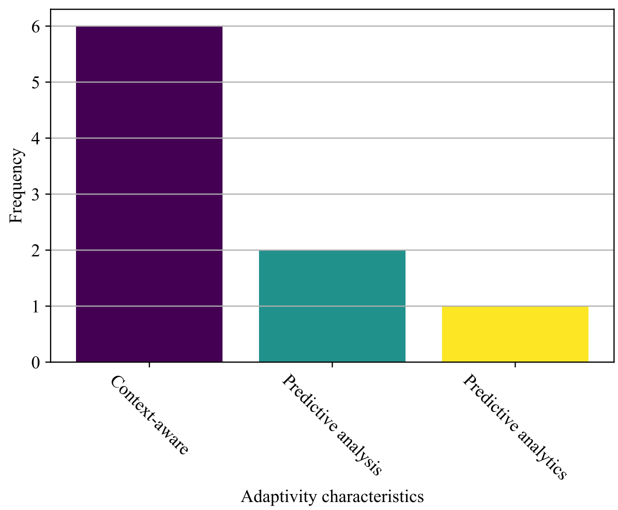

FIGURE 6. Frequency of adaptivity characteristics in adaptive waste management systems.

IV. ACHIEVING ADAPTIVE SYSTEMS

Despite the demonstrated progress and capabilities of the current urban systems landscape, the analysis of the literature in this domain indicates that there are common factors and potential innovations in adaptive systems that must be highlighted. Central to these aspects is the optimisation of data collection from urban sensing platforms and the integration of these data with powerful analytical methods. Such enhancements demonstrated to be essential for developing more responsive, efficient, and intelligent city services, which might proactively adapt to current conditions. This forward-looking approach will be instrumental in addressing the complexities of urban environments, where the dynamic interplay of various factors demands advanced data-driven solutions that are thoroughly integrated and seamlessly functional.

The recent advances in urban services in the context of sensing platforms have expanded the range of monitorable features, turning every urban element into a potential data source. This broad perspective, combined with the accessibility and affordability of powerful electronic devices, is transforming the development of smart cities. Indeed, the monitoring infrastructure is currently evolving from simply collecting data to contributing to the intelligent orchestration of city services, enabling urban systems to adapt to the ever-changing needs of their inhabitants. Nevertheless, in order to achieve these goals, it is evident that tailored sensing technologies and georeferenced data analysis are fundamental. Therefore, to better understand how such methods can help to develop practical systems (RQ3), this discussion section explores the four main technological aspects that foster a truly evolving urban ecosystem.

As illustrated in Figure 7, a typical adaptive framework seamlessly integrates multi-target sensors, edge computing,

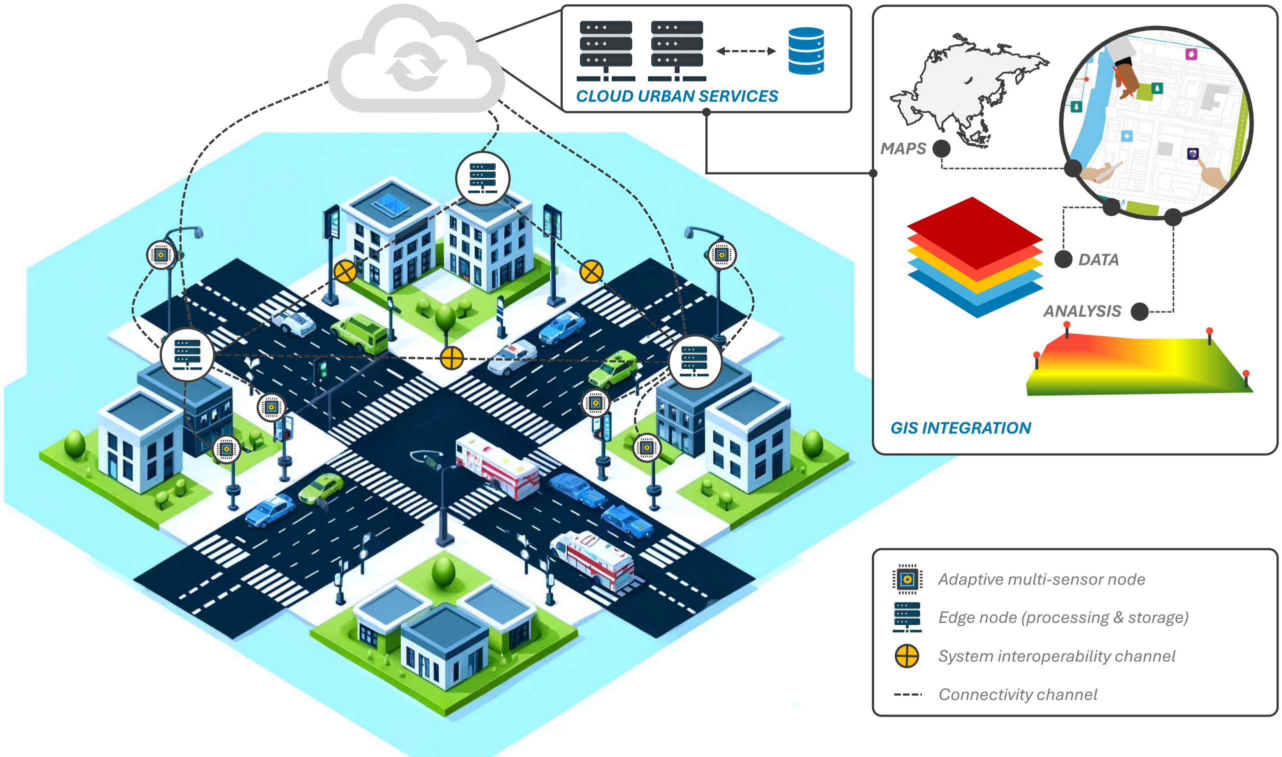

FIGURE 7. Schematic of a smart city adaptive framework, highlighting the integration of multi-target sensors, edge/cloud computing, and GIS for enhanced urban system interoperability.

and GIS technologies to enhance the operation of smart urban systems. This schematic representation demonstrates the synergy between these components, facilitating urban data processing and comprehensive geospatial analysis. This representation provides a foundation for a more detailed examination of the potential for adaptive technologies to be achieved across various domains, with the objective of fostering more resilient and responsive urban environments.

A. MULTI-TARGET SENSOR UNITS

As the smart city landscape evolves, using multi-target sensor units is a significant advance in the search for comprehensive urban monitoring and management [16]. These units can gather a wide array of parameters, optimising resource allocation and streamlining data collection processes. Multi-target platforms integrate various functionalities into a single efficient unit, unlike traditional systems that require separate data collection devices for each specific target monitoring [124]. This integration reduces the physical and economic burden of deploying numerous single-purpose devices and mitigates the complexity of managing a diverse sensor network. By embracing the versatility of such units, smart cities can take a more cohesive and dynamic approach to data collection, leading to a deeper understanding of urban ecosystems.

Expanding on the infrastructure built by heterogeneous sensor arrays, smart cities are now ready to further enhance their monitoring capabilities by developing adjustable architectures [125], [126]. These innovative frameworks increase the flexibility of sensor applications, allowing for the monitoring of a wide range of urban elements while keeping the pace of technology advances [124]. This adaptivity is particularly important to address the real nature of urban environments, where the demand for information can shift rapidly due to population dynamics, infrastructure development, or emergent environmental challenges.

Multi-target frameworks support the notion that a one-size-fits-all approach is no longer viable in the complex ecosystem of smart cities. These frameworks acknowledge the diversity in urban environments, ranging from the spatial layout and population density to the cultural and economic activities that define each city [127]. Therefore, by enabling the deployment of sensor units that can be adapted to monitor different urban attributes as city priorities shift, these platforms can monitor diverse urban parameters through a more cohesive system.

This progression towards adaptive sensor nodes represents a natural evolution in smart city technologies, emphasising not only the physical but also the functional versatility of sensor units and their ability to undergo tailored adjustments [5], [125]. The core advantage of these units lies in their capability to reduce deployment and upgrade costs. Traditionally, adapting a sensing infrastructure to new requirements or integrating other technologies requires the replacement or substantial modification of existing hardware and software, a process that is both time-consuming and costly [9]. Adaptive sensors reduce this need by streamlining the upgrade process and extending the lifespan of the sensor infrastructure, offering substantial cost savings over time [128].

Adaptive sensor units dynamically adjust configuration parameters such as calibration data or prioritisation rules to meet the application requirements [129], [130]. By using sensors that can adapt based on current urban demands or geolocalised environmental conditions, cities can implement a more nuanced and comprehensive monitoring strategy. This higher level of adaptivity enables efficient resource allocation, ensuring that sensing units can shift their attributes in response to the city's evolving needs.

The ability to adapt sensor nodes with minimal human intervention leads to optimal performance and reduced human effort in maintaining the infrastructure. For example, a sensor unit initially deployed for traffic management can be repurposed to monitor air quality during a pollution spike [131] or to relate this information with noise levels in streets infrastructure [132]. This flexibility maximises the potential of each sensor node, enabling cities to respond more swiftly and effectively to permanent or sporadic changes in the environment. However, to evolve according to current urban demands, these devices must incorporate the ability to securely modify their functionalities, using, for example, Over-the-Air (OTA) updates [133], [134]. Doing so, multi-sensor units are allowed to dynamically initialise, configure, and operate a wide array of sensors tailored to the specific needs of the urban environment. This feature also allows for seamless integration of additional sensors into the existing infrastructure as new monitoring needs arise.

From the perspective of urban systems, the benefits of adjustable sensor nodes are twofold. Firstly, they facilitate easy customisation of sensing infrastructure to address urban challenges such as environmental data collection or emergency management. This capability allows city managers to selectively deploy monitoring routines tailored to specific purposes, streamlining the process of gaining actionable insights and implementing responsive actions. Additionally, the incorporation of modularity into this infrastructure allows for the integration of new technologies or repurposing existing assets to meet the ever-changing urban needs. Therefore, as new sensor technologies emerge or urban priorities shift, the nature of these platforms ensures that the monitoring infrastructure can adapt without reengineering or prohibitive costs.

Finally, the scalability offered by these units is also essential for the sustainable development of smart cities [135]. By leveraging modular adjustable units, cities can begin with a basic sensor network and gradually expand by incorporating new modules as required by their growth strategies or as budget constraints allow. This incremental approach reduces the initial investment required to launch smart city initiatives [136], making them more accessible and feasible for municipalities of varying sizes and resources. However, as systems expand in size, it becomes necessary to provide mechanisms for their seamless operation, enabling the sharing of information as required.

B. INTEROPERABILITY

Interoperability in smart cities refers to the ability of various urban subsystems, such as energy, mobility, water, and waste management, to exchange and use information in a meaningful way [137]. At the application level, interoperability enables the development of smart urban solutions that can integrate data from multiple sources, process it, and provide decision support for urban planners and managers. As such, interoperability is the glue that holds urban systems together, enabling them to be more than the sum of their parts. Therefore, it enables these systems to provide efficient and user-focused services within smart cities, facilitating standardisation. Although it is considered a practical solution to achieve sustainable smart cities, our literature review reveals that this is still an underexplored domain.

Several classifications of interoperability exist [138]; however, it is important to consider the following two classes:

- Technical interoperability: ensures effective communication between different technology systems by adhering to common standards.
- Semantic interoperability: Focuses on understanding data across different systems by using shared vocabulary and ontology.

Technical interoperability is the fundamental layer that enables technological systems to communicate and operate cohesively [138]. It is based on the adoption of universally recognised standards and protocols, which ensure that hardware and software from different manufacturers or service providers can exchange data and share information seamlessly. For example, technical standards such as IEEE 1452, which supports smart transducer interfaces [139], and IEEE 1547, which governs the grid interconnection of distributed energy resources [140], facilitate the sensors' interoperability. Nevertheless, adherence to these standards is hindered by the high cost of compliance and the limited availability of compatible sensors, which makes it unfeasible to implement them on a large scale, such as in urban areas.

Additionally, technological interoperability can be achieved through network communication protocols such as MQTT (Message Queuing Telemetry Transport Technical) and CoAP (Constrained Application Protocol) [34]. These protocols are designed to support the low-power needs of IoT devices, ensuring efficient and standardised data transmission across the urban network. Moreover, the Open Geospatial Consortium (OGC) establishes standards for geospatial and location-based services [141]. In fact, the integration of geospatial data into urban monitoring allows adaptive urban systems to ensure that their components are not isolated, thereby fostering a synergistic environment in which integrated application-level services can thrive.

Semantic interoperability goes beyond data exchange and enters into the domain of meaning and context [137]. It guarantees that information shared between systems is understandable and actionable, regardless of the system that generated it. This level of interoperability relies on shared vocabulary and ontology, which provide a structured framework of terms and relationships that are crucial for data interpretation and utilisation in adaptive urban systems.

To achieve semantic interoperability, systems must apply the structure and syntax of information exchange by reusing or extending standards from established bodies such as W3C, OASIS, OMG, NIEM and HL7. It is also necessary to specify the rules for information assembly and processing in an unambiguous way. These rules should contain patterns for the aggregation of data and conversion transformations to shared agreement standards while also involving parsing messages into their data elements. For example, systems that use NGSI-LD (Next Generation Service Interfaces-Linked Data) can interpret and act on the information they receive [142]. This includes identifying that "temperature" in one system corresponds to the same entity in another. This level of interoperability is critical to supporting adaptive services, where data from different domains need to be processed together. To that end, integrating efficient and timely data processing mechanisms is crucial, leveraging advanced technologies to ensure seamless and responsive urban services.

C. CLOUD AND EDGE COMPUTING

In the rapidly evolving landscape of urban systems, cloud and edge computing emerge as pivotal technologies for reshaping the way cities are managed. Cloud computing, with its vast computational resources and scalable storage capabilities, provides a centralised platform for processing and managing the information generated by urban systems. On the other hand, edge computing brings data processing closer to the source, enabling real-time analytics and decision-making. Together, these technologies form the backbone of distributed adaptive urban systems, offering enhanced efficiency and reduced latency.

The role of cloud computing in improving the adaptivity of urban systems cannot be underestimated. Its inherent scalability and flexibility enable the efficient management and analysis of vast amounts of urban information. By leveraging cloud infrastructure, cities can scale their computing and storage resources to meet fluctuating demand without the need for significant investment in physical infrastructure. Cloud platforms provide the resources needed to perform advanced data analytics, notably supporting machine learning operation and sensor platform integration, enabling cities to adapt and manage the demands of urban life and deliver more responsive services.

However, due to the large scale of sensor network infrastructure, relying solely on cloud services is no longer practical. The amount of data that needs to be transmitted is continually growing, which can lead to network overload and compromise system reliability despite the scalability of cloud platforms [143]. In this context, edge computing emerges as a pivotal technology for enabling real-time adaptivity in urban systems, addressing the necessity for immediate data processing and response near the data source [144].

In smart cities, edge computing is materialised through a variety of devices and architectures, from smart traffic lights that adjust in real-time to optimise flow [78] to surveillance cameras with built-in analytics for immediate detection [145]. These devices possess the computational power to process data on-site, making decisions and taking actions without the need to constantly communicate with a cloud server. Furthermore, edge devices can incorporate machine learning applications, empowering them to learn and adapt to changing urban conditions [146].

In fact, cloud and edge computing play complementary roles, creating a seamless "backbone" of data processing capabilities that enhance the efficiency and adaptivity of smart cities. This synergy enables smart cities to leverage the strengths of both technologies: the edge for immediate responsiveness and reduced latency and the cloud for advanced analytics, broader context understanding, and resource-intensive computing tasks.

D. GEOSPATIAL DATA-DRIVEN ANALYSIS

To implement adaptive urban systems in a broader sense, new approaches to better understand a city need to be sought and developed. Extracting information about urban dynamics requires mechanisms that could be studied without collecting information from the whole city, revealing a situation where geospatial data-driven approaches are critical. By using data-driven methods, however, computational urban models can be developed to help understand this complex environment. While central to the implementation of future urban systems, advances in the integration of geospatial information with the potential capabilities of adaptive urban systems remain an open area of research. A central aspect of this transformation is the role of GIS in facilitating the study of adaptive requirements based on geographical urban assessments.

Due to their natural capability for retrieving, storing, manipulating and analysing georeferenced data, GIS has enabled a more comprehensive understanding and management of urban environments [147]. These systems have the ability to scale across a wide range of urban environments, from rural villages and cities to entire metropolises. The versatility of these systems extends to a wide range of applications such as mobility [148] and emergency management [149], [150]. Therefore, the integration of GIS with real-time urban data analytics can potentially improve urban situational awareness, demonstrating its ability to optimise decision-making in dynamic scenarios [151].

GIS technologies are based on the principle of georeferencing, which allows all data to be associated with precise geographic coordinates (latitude and longitude) [152]. In addition, GIS can be used in smart city applications to integrate data from public and private sources, which has a direct impact on the way such data are used in practical applications [153]. Moreover, the ability to calculate and visualise patterns in city services plays a key role in urban systems [60]. This function helps to identify trends and assists city planners in crafting resource allocation strategies. Moreover, when combined with sensor technologies, GIS becomes even more powerful in assessing dynamic urban environments [154].

It is worth mentioning that although the literature does not directly relate GIS to the development of adaptive urban systems, these tools are an integral part of their sustainable implementation by providing spatial intelligence and analytical tools. In fact, GIS can be used effectively to overcome the obstacles that arise and provide essential support for the development of adaptive solutions, given the multifaceted nature of the data processed and the analysis performed.

The integration of GIS with data analytics tools can facilitate the monitoring and management of urban growth and transformations. By continuously updating data layers with information from sensors and other data sources, GIS can provide a better dynamic assessment of urban conditions, from traffic patterns to energy consumption and environmental monitoring. This continuous flow of geospatial data allows city planners and decision-makers to anticipate changes rather than simply reacting to them, thereby enhancing the proactive capabilities of smart city systems. Furthermore, GIS can support the simulation and visualisation of urban development scenarios, providing a valuable tool for urban planners to foresee the impacts of different planning decisions. This capability not only aids in better resource management but also ensures that the adaptive urban systems are aligned with the long-term sustainability goals of the city.

Finally, the adoption of GIS tools can be further integrated into the concept of Digital Twins (DT), a remarkable resource when pursuing adaptive urban systems. Digital twins serve as virtual replicas of physical entities and processes, providing a dynamic platform for simulating, predicting, and optimising urban operations [155]. By incorporating GIS data into DT, urban planners can achieve a more granular understanding of spatial relationships and dynamics across the cityscape [108]. This integration facilitates enhanced scenario planning and decision-making by allowing city administrators to visualise the impacts of various strategies in a controlled virtual environment before implementation. Additionally, it can drive more tailored, location-specific solutions in real-time, adapting to changes as they occur in the urban fabric.

V. OPEN CHALLENGES AND FUTURE DIRECTIONS

The development of smart cities involves a complex framework of technological innovations that support the delivery of urban services. The integration of monitoring platforms, network infrastructure, and GIS data analytics may enable these services to respond, adapt, and evolve in accordance with the urban landscape. The significance of these technologies lies not only in their individual capabilities but also in how they converge to create a synergistic effect that transforms static urban fabrics into responsive entities. Consequently, it is imperative to comprehend the interactions of these technologies with current applications to identify how adaptive urban systems can transcend traditional boundaries and offer a new paradigm of sustainable and oriented living experiences. Nevertheless, although the literature demonstrates potential advancements associated with the development of dynamic urban services, several challenges remain to be considered.

The practical benefits of recent implementations of adaptive urban systems have been demonstrated, thereby reinforcing the theoretical insights discussed in this paper. A study indicated that the implementation of an adaptive traffic signal control system in a major urban area could result in an 80% reduction in average waiting times [78]. Furthermore, the integration of real-time data analytics and edge computing has resulted in energy savings of up to 80% through the utilisation of an adaptive street lamp system [11]. Interoperability between emergency management and mobility systems has also been beneficial for emergency vehicles, with priority given to these vehicles in certain instances [103]. In this case, the potential reduction in waiting times for such vehicles at the traffic lights is demonstrated. In the context of waste management, the deployment of adaptive sensor-equipped bins has been shown to reduce the energy consumption of smart waste bins by 34% while simultaneously enhancing overall service delivery and environmental sustainability [118]. These examples serve to illustrate the tangible benefits of adaptive systems, validating their potential to transform urban service delivery.

The analysis of adaptivity applications across various domains of smart urban services reveals several common themes and areas for future research. The prevalence of context-awareness, predictive analytics, and self-configuration underscores the critical role of real-time data utilisation and autonomous decision-making in enhancing the resilience and efficiency of smart urban systems. The analysis identified the lower preponderance of self-healing mechanisms as a potential avenue for future research and development across all surveyed domains. Incorporating self-healing mechanisms could reinforce the resilience of urban systems by enabling autonomous fault detection and rectification, reducing downtime, and facilitating continuous operation.

Our findings also indicate that the integration of IoT, machine learning, and Big Data analytics has been paramount for adaptive urban systems. These technologies facilitate data processing and decision-making, which are indispensable for adaptive services. The adaptivity strategies have been successfully demonstrated in urban service domains such as energy, mobility, and emergency management. However, despite the potential benefits, several challenges hinder the widespread adoption of adaptive systems. These challenges include data integration issues, real-time processing requirements, and the lack of interoperability.

The progression from adjustable entities towards adaptive sensor nodes represents a natural evolution in urban systems technologies, emphasising not only the physical but also the functional versatility of sensor units and their ability to undergo tailored adjustments. The core advantage of these units lies in their capacity to significantly reduce deployment and upgrade costs. Traditionally, as previously discussed, adapting a sensor network to new requirements or integrating other technologies requires the replacement or substantial modification of existing hardware, a process that is both time-consuming and financially burdensome. In parallel, adaptive sensor units must reduce the necessity for physical alterations or replacements, streamlining the upgrade process and extending the lifespan of the sensor infrastructure. Doing so could result in savings over time, not only in terms of adjusting the monitoring capabilities but also in adapting its operational characteristics dynamically.

Integrating such emerging technologies with GIS presents significant challenges, yet it is crucial for advancing the adaptivity and responsiveness of smart city infrastructures. One major challenge is ensuring interoperability among diverse systems that handle different data formats and standards. GIS systems, designed to manage and analyse spatial data, must effectively synchronise with electronic devices that provide data streams and machine learning algorithms that process and predict urban dynamics. Moreover, maintaining data integrity and accuracy across these platforms is critical since the decision-making processes in smart cities heavily rely on the precision of geospatial and monitoring (sensors-based) data.

One of the most significant challenges in incorporating adaptivity into urban systems relates to the dynamic nature of urban fabric. Efficient systems must be able to accommodate the continuous flux of urban conditions, analysing how variables change across different areas of the city and over time. This requires sophisticated data models that can handle large volumes of information collected from diverse sources, including sensors spread across an urban landscape. Integrating these data to accurately reflect the spatial distribution and temporal variation demands solutions capable of predictive analytics and processing. Furthermore, the systems must be scalable and flexible, capable of adjusting to new configuration data inputs and shifting urban monitoring and actuating patterns without compromising performance. This challenge lies in the technical implementation of such systems and in ensuring that they can operate efficiently under the constraints of existing and future urban infrastructure.

Incorporating such a spatiotemporal analysis into urban systems would allow cities to dynamically manage traffic, optimise public safety responses, monitor environmental conditions, allocate resources effectively, and guide urban development with greater precision. For example, traffic management on a given street can be fine-tuned based on vehicular flow and the information on the urban assets during rush hours, leading to smoother commutes and reduced congestion. Similarly, analysing crime or accident data over time and space helps in preemptively deploying emergency services to hotspots, thus improving public safety. Furthermore, resource management, such as waste collection, can be optimised by understanding usage patterns based on population density across different city sectors and time frames. Actually, it is expected that urban planning will benefit from these analyses by facilitating data-driven decisions that accommodate the changing needs and growth patterns of urban populations.

While this technological movement towards more responsive urban systems promises enhanced urban efficiency, it also introduces significant ethical and social challenges. Central among these is the pervasive monitoring required to gather the data that fuels these systems, which raises concerns about privacy and the potential for surveillance overreach. This extensive data collection must be managed carefully to respect individual privacy rights and adhere to ethical standards, which necessitates robust regulatory frameworks and transparent data handling practices. Furthermore, there is a significant risk of exacerbating existing inequalities through these technological enhancements. In fact, the benefits of smarter urban services, such as improved mobility, enhanced public safety, and more efficient resource management, may not be equitably distributed across all urban populations. This disparity could result in a scenario where access to essential services, which are increasingly mediated by digital technologies, would become a function of one's socioeconomic status.

Therefore, addressing these challenges requires a proactive focus on inclusivity and fairness when deploying these systems. Policies must be crafted to ensure these technologies are accessible to all, regardless of economic status, and efforts should be made to boost digital literacy across the board. Furthermore, the development of adaptive urban systems must include mechanisms to monitor and correct any imbalances in service distribution, ensuring that all residents can benefit from the advances in urban living. These strategies are of paramount importance for the ethical deployment of smart urban technologies and for fostering public trust and acceptance, which are crucial for the successful implementation of these systems.

To fill these and other research gaps, we have identified potential future research opportunities that should guide new developments in this area.

- Despite the progress in integrating GIS with sensing infrastructure and machine learning methods, there is a need for more advanced methodologies that seamlessly blend these paradigms to provide dynamic real-time urban management solutions. Future research could focus on developing interoperable frameworks that allow for smoother data exchange and processing across these platforms to allow holistic system adaptation.

- With the increase in data-centric urban management solutions, safeguarding privacy and enhancing data security are paramount. In fact, adaptive systems will rely on the exchange of sensitive information that interferes with the overall operation of the service. Therefore, studies that investigate new authentication methods and robust security protocols specifically tailored for interconnected networks of smart cities are needed.
- Exploring the impacts of adaptive urban systems is crucial, especially in light of global sustainability goals. Future studies could focus on developing assessment metrics that guide the adaptivity of those systems. Encouraging interdisciplinary research that combines urban planning, information technology, sociology, environmental science, and public policy can lead to more holistic and effective smart city solutions.
- As smart city technologies advance, it is crucial to ensure that these innovations reach all segments of the population. New research could explore strategies for deploying urban tech solutions that bridge the digital divide, ensuring disadvantaged and less digitally literate communities benefit equally from urban developments.

VI. CONCLUSION

The integration and evolution of adaptive urban systems represent a significant step in positively transforming our cities into better places to live. This survey article has provided a review of the state-of-the-art technologies and methodologies that underpin the adaptivity of urban services across various domains, which is a promising concept for improving our cities. By exploring these areas through a lens of advanced technological frameworks, this paper has highlighted the pivotal role that integrated systems play in fostering adaptive and responsive urban environments. Throughout this review, we have examined methods that emphasise the convergence of geospatial analytics with urban data processing technologies, which is crucial for enhancing the operational adaptivity of city infrastructures to the ever-changing urban conditions.

Overall, this article has showcased how urban systems can become more efficient, proactive, and sensitive to the needs of their diverse populations. However, while this article has outlined a range of innovative applications and the potential of adaptive urban systems, the journey towards fully realising these capabilities is still ongoing. As a major conclusion, it is reasonable to say that the future of urban development lies in harnessing the power of technology to create environments that are not only smart but also sustainable, inclusive, and resilient, with the acquisition and processing of heterogeneous spatiotemporal data at their core.

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JOÃO CARLOS N. BITTENCOURT (Member, IEEE) received the M.Sc. degree in electrical engineering from the Federal University of Bahia, Brazil, in 2017. He is currently a Professor with the Centre of Exact and Technological Sciences (CETEC), Federal University of Recôncavo da Bahia, Brazil. His research interests include integrated circuits digital design, embedded systems, the Internet of Things applications, and smart cities.

DANIEL G. COSTA (Senior Member, IEEE) received the M.Sc. and Ph.D. degrees in electrical and computer engineering from the Federal University of Rio Grande do Norte, Brazil, in 2006 and 2013, respectively. He was an Associate Professor with the State University of Feira de Santana, Brazil, until 2022. He is currently an Assistant Professor with the Electrical and Computer Engineering Department (DEEC), Faculty of Engineering (FEUP), University of Porto, Portugal, and an Associated Investigator with SYSTEC. He is the author or co-author of more than 150 international articles in the areas of embedded systems, computer networks, the Internet of Things, smart cities, and sensor networks.

PAULO PORTUGAL (Member, IEEE) received the Licentiate, M.Sc., and Ph.D. degrees in electrical and computer engineering from the University of Porto, Portugal, in 1992, 1995, and 2005, respectively.

Currently, he is an Associate Professor with the Department of Electrical and Computer Engineering, University of Porto. He is the author or co-author of more than 130 technical articles in the areas of industrial communication systems, communication networks for embedded systems and dependability modeling, and evaluation of safety-critical systems. He supervised or co-supervised eight Ph.D. and more than 70 Master's theses. He has teaching experience in more than 30 courses, covering subjects, such as industrial automation, industrial communications, discrete event systems modeling, safety-critical systems, instrumentation, and electronics.

FRANCISCO VASQUES received the Ph.D. degree in computer science from LAAS-CNRS, Toulouse, France, in 1996.

He has been an Associate Professor with the University of Porto, Portugal, since 2004. He is the author and co-author of more than 150 articles in the areas of real-time systems and industrial communication systems. His current research interests include real-time communication, industrial communication, and real-time embedded systems. He has been a member of the Editorial Board of *Sensors* and MDPI, for the Sensor Networks Section, since 2018, and *International Journal of Distributed Sensor Networks* (Hindawi). He has been an Associate Editor of IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS for the topic of Industrial Communications, since 2007.