www.editada.org

International Journal of Combinatorial Optimization Problems and Informatics, 17(4), 2026, 94-104. ISSN: 2007-1558.
https://doi.org/10.61467/2007.1558.2026.v17i4.1297

An AI-Enabled Smart City Architecture for Monitoring and Specialised Care of People with Sarcopenic Obesity

Irahan-Otoniel José-Guzmán[1] and Mirta Fuentes-Ramos[1]

[1] Artificial Intelligence Lab of National Tech. Misantla, Veracruz, Mexico
✉Corresponding author: mirta.fura@gmail.com

Abstract. Smart cities can contribute to public health through digital monitoring systems, telemedicine services, efficient emergency management, and data-driven decision-making. Sarcopenic obesity, characterised by the coexistence of obesity and loss of muscle mass, represents an emerging public health challenge that requires continuous monitoring and specialised care. This study proposes a conceptual smart city architecture for monitoring and supporting people with sarcopenic obesity. The proposed architecture integrates hardware-based monitoring technologies with artificial intelligence software to facilitate access to healthcare services, support remote care, and enable data-informed decision-making. By combining technological infrastructure and artificial intelligence within a smart city framework, the conceptual model seeks to improve the coordination and accessibility of specialised healthcare and contribute to the quality of life of people living with sarcopenic obesity. The main contribution of this study is an integrated conceptual architecture that connects digital monitoring, telemedicine, artificial intelligence, and specialised care within a smart city environment. Future research should evaluate its technical feasibility, clinical applicability, privacy requirements, usability, and effectiveness in real-world healthcare contexts.
Keywords: smart city architecture; sarcopenic obesity; artificial intelligence in healthcare; digital health monitoring; telemedicine; smart healthcare; specialised healthcare; data-driven decision-making; quality of life.

Article information

Received: Jan 11, 2026
Accepted: May 19, 2026

1 Introduction

A smart city integrates digital technologies, connectivity, and data analysis to improve the quality of life of its inhabitants, optimize the use of resources, and strengthen urban sustainability. Through sensors, smart platforms, and interconnected systems, a smart city efficiently manages key areas such as transportation, energy, the environment, security, and public services (Batty et al., 2012). In the field of human healthcare, a smart city applies these technologies to strengthen health systems through prevention, early diagnosis, and continuous monitoring of diseases. The use of smart medical devices, digital medical records, telemedicine, and real-time data analysis allows for personalized medical care, improved emergency response, and optimized hospital management (Rocha et al., 3019).

Sarcopenic obesity is a condition defined by the coexistence of excess adipose tissue and loss of muscle mass and function (Polyzos & Margioris, 2018). This condition increases the risk of frailty, disability, and premature mortality (Barazzoni et al., 2018). Its pathophysiological mechanisms include chronic low-grade inflammation, insulin resistance, and mitochondrial dysfuncyion (Cauley, 2015). The combination of obesity and sarcopenia exacerbates metabolic deterioration and limits functional capacity (Choi, 2016). It is recognized as an emerging public health problem due to population aging and the rise in obesity (Zamboni et al., 2008). Early identification is essential to prevent clinical complications. A multidisciplinary approach is necessary to mitigate its health and socioeconomic impact.

© Editorial Académica Dragón Azteca S. de R.L. de C.V. (EDITADA.ORG), All rights reserved.

A smart city architecture can help alleviate sarcopenic obesity through sensors, wearable devices, and data platforms (Temeljotov-Salaj & Bogataj, 2021; Glebova & Desbordes, 2022). The city can monitor the population's physical activity patterns, mobility, and lifestyle habits, allowing it to identify at-risk groups and design personalized preventive interventions. Likewise, the integration of telemedicine, digital medical records, and remote monitoring programs can be used to evaluate key indicators such as muscle mass, strength, mobility, and body composition. Real-time data analysis allows healthcare professionals to tailor exercise, nutrition, and rehabilitation plans on an individual basis, as well as coordinate actions between primary care, social services, and community centers. In this way, the smart city not only addresses sarcopenic obesity from a clinical perspective, but also from a preventive and social perspective, promoting active aging and a better quality of life.

The rest of the article is divided as follows: Section 2 mentions related work and analyzes the opportunity niche based on a SWOT analysis. Section 3 describes what a smart city is and shows the elements that make up a general architecture. Both obesity and sarcopenia are described in Section 4. Section 5 proposes a smart city architecture for the identification, monitoring, and medical treatment of sarcopenic obesity. The challenges to be overcome and the philosophical aspects to be analyzed are explored in depth in section 6. Finally, the authors' conclusions on the proposed conceptual model are mentioned in section 7.

2 Related works

Zhang et al. (2025) evaluated sarcopenia using a novel approach based on machine learning and wearable Internet of Things (IoT) sensors. To construct the database, 53 adults aged over 65 years underwent gait analysis using dual sensors that extracted 19 features. Classification algorithms were implemented to categorise participants as healthy, at-risk level 1, at risk level 2, or at-risk level 3 for sarcopenia, resulting in four classes and an average performance of 94.67%. The authors also performed a binary classification of healthy individuals and those at risk of sarcopenia, achieving an average performance of 97.41%.

Gong et al. (2023) evaluated obesity research through a bibliometric study of 3,286 publications indexed in Web of Science between 2004 and 2023 that addressed the use of machine learning. The most representative approaches were deep learning, support vector machines, and predictive models, and exponential growth in scientific output was identified. The United States led scientific production in this field, Leo Breiman was identified as the most influential author, and *Scientific Reports* was the most productive journal. “R: A Language and Environment for Statistical Computing” was identified as the most frequently cited work. Emerging research areas included gut microbiota, energy expenditure, genomics, COVID-19, and diabetic retinopathy.

Bernal et al. (2024) examined human ageing as a complex biological process influenced by multiple factors and as a growing challenge in societies with ageing populations. The authors conducted a systematic review of 77 articles addressing the use of artificial intelligence in ageing research. The most frequently used approaches were machine learning and deep learning, applied to imaging, genomic, behavioural, and contextual data. The results showed that artificial intelligence (AI) can predict age-related outcomes, support biomarker development, and identify factors associated with healthy ageing. However, challenges related to data quality, model interpretability, ethics, and privacy were also identified.

An et al. (2022) evaluated the application of artificial intelligence to obesity, a major cause of preventable mortality, by reviewing 46 articles that used AI to measure, predict, or treat this condition. Machine learning and deep learning algorithms were applied to tabular, image, and textual data. Most of the comparative studies—18 of 22, or 82%—reported higher predictive accuracy for AI than for conventional statistical methods, whereas 5 of the 46 studies, or 11%, reported mixed results. The review also identified a growing trend towards next-generation deep learning models for complex computer vision and natural language processing tasks. AI enabled the identification of clinically relevant patterns and associations between covariates and weight-related outcomes, thereby supporting obesity research and management.

Ribeiro et al. (2021) evaluated the association between inflammation, obesity, and muscle strength in 247 adults aged 60 years or older who were at risk of dynapenia and sarcopenia. Dynapenia was diagnosed according to the European Working Group on Sarcopenia in Older People 2 criteria, and multivariate quantile regression was used to analyse the relationship between inflammatory cytokines and muscle strength. The results showed that 74.4% of participants with dynapenia were men and that this group had elevated interleukin-10 levels of 0.95 pg/mL and reduced handgrip strength. Obesity was more prevalent among participants without dynapenia, at 45.3% (95% CI [37.7, 53.0]). A significant negative association was identified between interleukin-10 and muscle strength, demonstrating the interaction among inflammation, obesity, and dynapenia.

Bedrikovetski et al. (2022) evaluated the use of automated muscle segmentation in computed tomography scans for body-composition analysis and sarcopenia diagnosis. The authors reviewed 24 studies, 15 of which used deep learning to automate segmentation. The models analysed skeletal muscle, subcutaneous adipose tissue, visceral adipose tissue, and bone across different study populations. The quantitative results showed a pooled Dice similarity coefficient of 0.941 for skeletal muscle and values ranging from 0.963 to 0.970 for adipose tissue and bone, indicating high segmentation accuracy. These findings suggest that AI-based models can support body-composition assessment and sarcopenia diagnosis.

Onishi et al. (2025) evaluated automated muscle-mass measurement in computed tomography scans for the diagnosis of sarcopenia. The authors analysed 3,096 cases involving images acquired at the level of the third lumbar vertebra between 2011 and 2021. AI models were developed for body-region detection using DeepLabv3 and for sarcopenia diagnosis using EfficientNetV2-XL. The diagnostic model achieved a sensitivity of 82.3%, specificity of 98.1%, and positive predictive value of 89.5%, whereas the body-region detection model achieved an intersection over union of 0.93. These results indicate that AI may provide a reliable and efficient alternative to conventional measurement methods.

Lauretani et al. (2023) assessed the increasing prevalence of sarcopenia associated with population ageing and its role as a contributor to disability. The study analysed a representative cohort from the Chianti region of Italy comprising older adults without neurological disorders. Indicators included isometric knee torque, handgrip strength, lower-limb muscle power, and calf muscle cross-sectional area. Sarcopenia was defined using values below the established reference mean. The results showed that its prevalence increased with age in both sexes, with greater age-related changes in muscle power and smaller changes in calf muscle area. The authors also identified clinical cut-off values for the early detection of reduced mobility and highlighted handgrip strength as a cost-effective marker suitable for clinical practice.

Timmins et al. (2018) examined the limited incorporation of big data into obesity research despite its potential applications in medicine and public health. The study considered information derived from retail sales, transportation, social networks, wearable devices, and commercial weight-management programmes. Relevant applications were identified through database searches and narrative analysis. The findings demonstrated the usefulness of big data for estimating nutrient purchases, characterising environments, and evaluating interventions, although important ethical and methodological limitations remained.

2.1 Niche of opportunity

Sarcopenic obesity is emerging as a health problem that can manifest as early as age 30, but the scientific literature has focused almost exclusively on older adults (>= 60 years). This creates a critical gap in early detection and understanding of the pathophysiological mechanisms in younger populations. AI, using machine learning algorithms, deep learning, IoT sensors, and big data analytics, has shown high diagnostic and predictive accuracy in older cohorts. However, its application in adults aged 30 to 50 is still in its early stages and represents an opportunity to advance toward preventive and personalized strategies. This gap is best analyzed in the SWOT analysis in Table 1.

Table 1. SWOT analysis of related works with sarcopenic obesity and AI.

Strengths	Opportunities	Weaknesses	Threats
Al models with high diagnostic accuracy in sarcopenia (94.7%]) and binary classification (97.4%).	Extend the application of AI to cohorts of young adults (>=30 years) for early detection.	Little or no evidence in patients aged 30-50 years; most studies in adults >=60 years.	Ethical, legal and privacy risks in the handling of big data and sensitive clinical data.
Deep learning in medical images achievesrobust metries (DSC >= 0.941; IoU=0.93).	Integration of ubiquitous computing, wearable sensors and microbiota/genomics data for personal ized medicine.	Lack of methodological standardization and heterogeneity of databases.	Gaps in Access to advanced technology in low-resource health systems.
Al outperforms conventional statistical methods in predicting obesity and sarcopenia (>=82% accuracy).	Development of digital biomarkers and prediction algorithms aplicable to clinical practice.	Limited interpretability of blackbox models annd biases in studied populations.	Clinical and regulatory resistance to the adoption of AI and ubiquitous computing in routine on-site diagnosis.
Identification of	Generate longitudinal cohorts	Dependence on large	

inflammatory and clinical patterns associated with muscle strength and osesity.	in Young people to validate predictive models.	volumes of High-quality multidimensional data,

3 Smart Cities Infrastructure

The infrastructure of a Smart City is based on an integrated technological ecosystem that combines physical devices, communication networks, digital platforms, and data analysis systems, with the aim of optimizing urban management, improving quality of life, and ensuring sustainability. This infrastructure can be divided into five layers (Fig. 1):

1. Physical layer (sensors and actuators): Includes IoT devices distributed throughout the urban environment, such as:
    - Environmental sensors (air quality, noise, temperature, humidity).
    - Traffic and mobility sensors (cameras, LIDAR, occupancy sensors).
    - Smart meters (electricity, water, gas).
    - Structural sensors in buildings and bridges.
    - Actuators such as smart traffic lights, dimmable LED lighting, and automated irrigation systems.

These devices capture data in real time and execute automatic actions according to predefined rules.

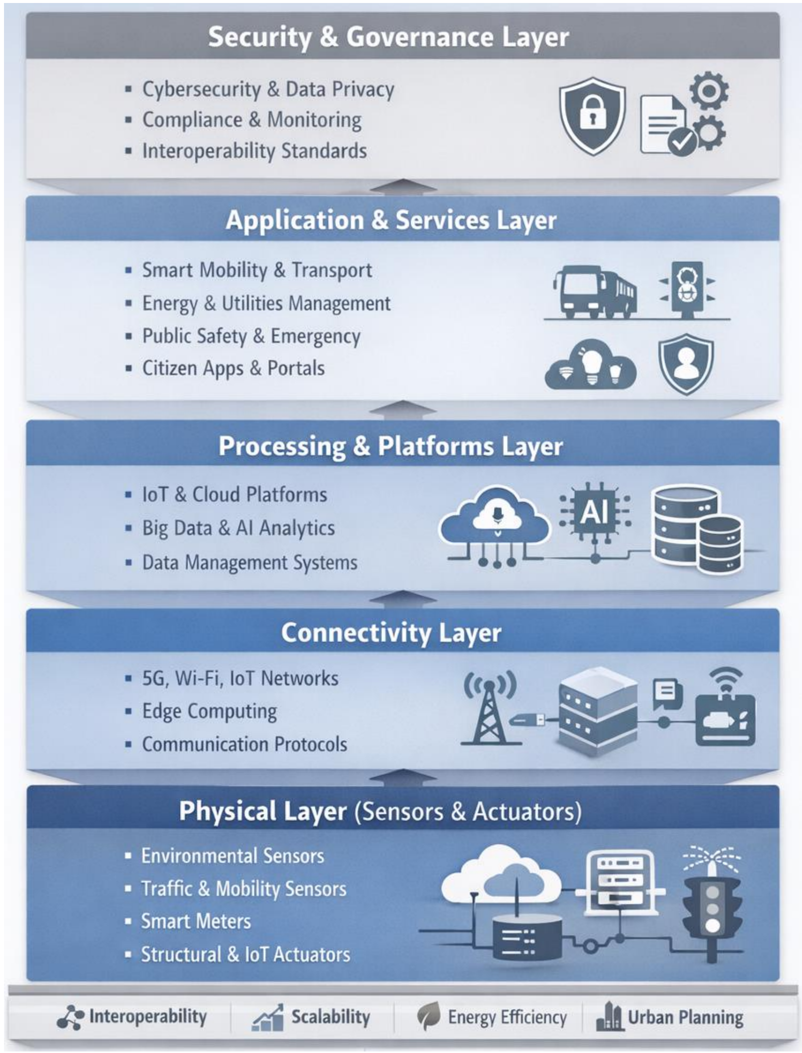

Fig. 1. The 5 layers of a smart city infrastructure.

2. Connectivity layer: This provides communication between devices and platforms, including:
   - Short- and long-range networks: Wi-Fi, Ethernet, 4G/5G, NB-IoT, LoRaWAN.
   - Communication protocols: MQTT, CoAP, HTTP/HTTPS.
   - Edge computing infrastructure for local processing and latency reduction.

This communication ensures low latency, high availability, and scalability.

3. Processing layer and platforms: Includes central management and analysis systems, such as:
   - IoT platforms for data ingestion and management.
   - Cloud (IaaS, PaaS, SaaS) and hybrid infrastructure.
   - Big data systems and databases (SQL and NoSQL).
   - Advanced analytics and artificial intelligence engines for prediction and optimization.

Enables cross-sector data correlation and real-time decision-making.

4. Application and service layer:
   - Intelligent traffic and public transport management.
   - Energy efficiency and smart grid systems.
   - Waste and water management.
   - Security and emergency response platforms.
   - Portals and mobile applications for citizen participation.

Provides digital services to citizens, businesses, and administrations.

5. Security and governance layer:
    - Cybersecurity (encryption, authentication, access control).
    - Data protection and privacy (regulatory compliance).
    - Monitoring, auditing, and operational continuity systems.
    - Interoperability frameworks and open standards.

    Ensures reliable system operation.

The five layers above enable infrastructure integration and sustainability in four areas:

1. Interoperability between different providers and systems.
2. Scalability in line with urban growth.
3. Reduced energy consumption and carbon footprint.
4. Facilitation of data-driven urban planning.

4 Sarcopenic obesity

Sarcopenic obesity is a clinical phenotype characterized by the coexistence of excess adipose tissue and loss of muscle mass and quality, whose interaction generates high-impact metabolic and functional alterations (Polyzos & Margioris, 2018). As illustrated in the Fig. 2, this condition results from the combination of obesity and sarcopenia, represented by a conceptual balance that reflects the imbalance between adiposity and skeletal muscle. At the tissue level, there is a reduction in muscle area accompanied by intramuscular fat infiltration, which impairs muscle contractile function and metabolic capacity.

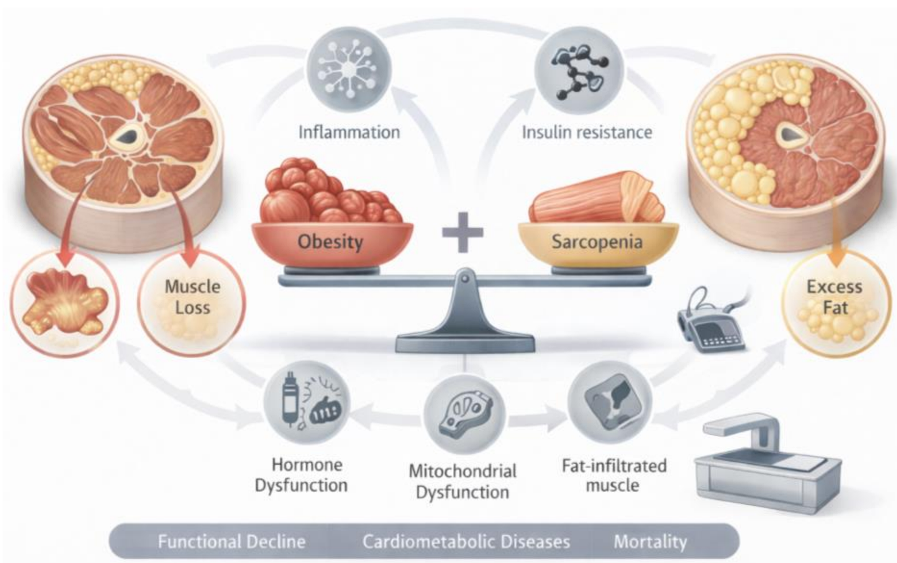

Fig. 2. Graphic (medical) description of sarcopenic obesity.

From a pathophysiological point of view, sarcopenic obesity is mediated by low-grade chronic inflammation, insulin resistance, mitochondrial dysfunction, and hormonal alterations, mechanisms that feedback on each other and accelerate muscle loss while promoting the accumulation of ectopic fat. Adipose infiltration of muscle further contributes to metabolic dysfunction and decreased strength, even in the presence of high body weight (Koliaki et al., 2019).

These structural and metabolic alterations are associated with functional decline, increased risk of cardiometabolic diseases, and increased mortality, as summarized in the clinical outcomes shown at the bottom of the Fig, 2. The diagnosis of sarcopenic obesity requires an integrated assessment of body composition and muscle function, using tools such as dual-energy X-ray absorptiometry, bioimpedance, or imaging techniques, along with functional tests. Overall, sarcopenic obesity is a major clinical and public health challenge that requires multidimensional therapeutic strategies focused on exercise, nutrition, and metabolic control (Lu et al., 2013).

5 Smart city architecture for identification of sarcopenic obesity

In this section, we propose a conceptual model for treating sarcopenic obesity in the context of a smart city (Fig. 3), based on biomedical sensors and machine learning (Wenge et al., 2014; Pribyl et al., 2018; da Silva et al., 2013). In the diagram, a study subject wears smart devices (watch and cell phone) that continuously monitor physiological and functional parameters. The data is analyzed in real time and transmitted to a smart hospital, where clinical alerts are generated when anomalies are detected. The system integrates the coordinated response of emergency services, pharmacies, and family members, facilitating timely intervention. In summary, an interoperable digital health ecosystem is defined that is geared toward early detection, continuous monitoring, and optimization of clinical care, which has an eight-axis care flow in the event of an emergency in a smart city.

Fig. 3. Smart city architecture proposed for identification of sarcopenic obesity.

1. Continuous monitoring: The patient wears smart devices (watch and cell phone) that continuously record physiological variables (heart rate, heart rate variability, physical activity, mobility patterns) and functional variables associated with sarcopenic obesity.
2. Data acquisition and transmission: The data captured by the sensors is transmitted securely, via wireless networks, to a digital health platform integrated into the smart city infrastructure.
3. Machine learning analysis: Machine learning algorithms process the information in real time to identify deviations from baseline patterns, estimate clinical risk, and detect potentially critical events (falls, extreme fatigue, cardiometabolic decompensation).
4. Clinical alert generation: When predefined risk thresholds are exceeded, the system automatically triggers an emergency alert, which is sent to the smart hospital and the medical services coordination center.

5. Clinical validation and prioritization: Healthcare personnel receive the alert along with the patient's medical history and validate the event, prioritizing care according to the estimated severity and associated comorbidities.
6. Activation of medical response: An ambulance is dispatched immediately and, if necessary, additional resources such as medical drones are enabled for the delivery of supplies or initial support.
7. Communication with support network: The system simultaneously notifies family members or caregivers via mobile apps or video calls, informing them of the situation and the actions being taken.
8. Coordination with pharmacy and follow-up: If pharmacological treatment is required, a prescription alert is generated to the linked pharmacy, while the system continues to monitor and record the event for clinical analysis and continuous improvement of the predictive model.

5.1 Feasibility analysis

The viability of the proposed architecture for identification of sarcopenic obesity within a smart city environment can be assessed from four main dimensions: technological, operational, economic, and ethical-regulatory.

Technological feasibility: The architecture has a high level of feasibility because its main components already exist and have reached a significant degree of technological maturity. Wearable devices capable of measuring heart rate, heart rate variability, physical activity, and mobility patterns are available commercially and feature clinically validated biometric sensors. Likewise, wireless connectivity infrastructures (4G, 5G, Wi-Fi, and IoT) enable continuous real-time data transmission, an essential requirement of the model. The use of machine learning algorithms for anomaly detection and clinical risk estimation is also technically feasible given current advances in predictive analytics. Therefore, architecture does not depend on experimental technologies, but rather on the interoperable integration of existing technologies.

Operational feasibility: Operationally, it is feasible provided there is interoperability between health systems, emergency services, and urban digital platforms. A coordinated eight-stage flow is proposed that reflects real clinical processes: monitoring, medical validation, prioritization, and care response. In addition, the inclusion of family support networks and pharmacies strengthens continuity of care, reducing response times and improving therapeutic adherence. However, operability depends on key organizational factors, such as staff training, standardized response protocols, and efficient alert management to avoid alert fatigue.

Economic feasibility: The model has moderate-high viability in gradual implementation schemes. Although the initial investment includes digital infrastructure, platform integration, and algorithmic development, much of the required hardware already belongs to the end user (smartphones and smartwatches), which significantly reduces costs. The main economic benefit lies in the prevention and early detection of complications associated with sarcopenic obesity, a condition linked to frequent hospitalizations, functional disability, and high healthcare costs. Additionally, the model favors preventive medicine strategies, which have proven to be more cost-effective than traditional reactive approaches.

Feasibility ethical-regulatory: Implementation requires strict compliance with regulatory frameworks related to privacy and biomedical data protection and informed consent. Continuous monitoring involves the mass collection of sensitive information, so encryption, anonymity, and access control mechanisms based on international digital health standards must be applied. From a social perspective, user acceptance is a critical success factor. Risks associated with digital divides must be considered, especially in populations with limited technological access or low digital literacy.

5.2 Reproducibility architecture.

To ensure reproducibility, scalability, and real-world deployment feasibility, the proposed smart city architecture incorporates a standardized block-based data flow model defining system interfaces, interoperability protocols, and security mechanisms (Fig. 4). The architecture specifies how physiological data move from sensing devices to clinical decision systems through well-defined communication layers and standardized healthcare data formats.

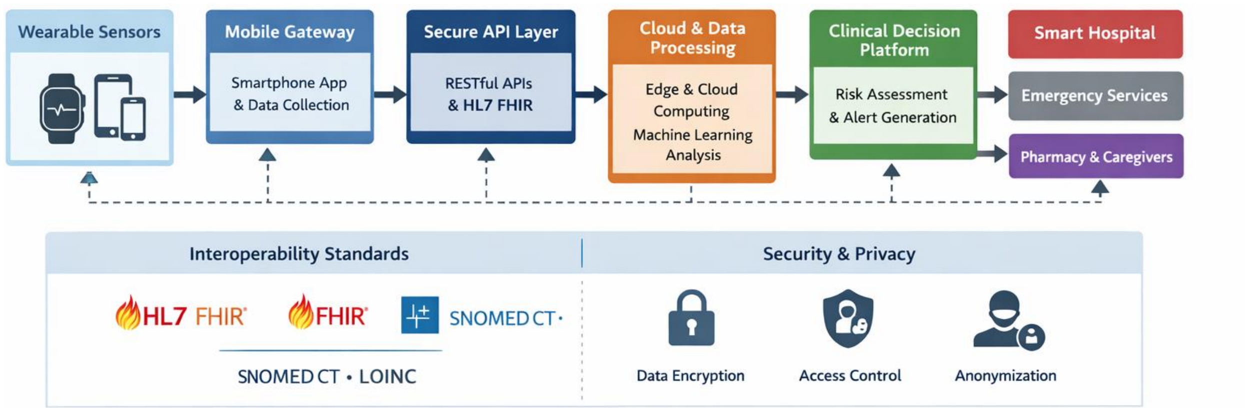

Fig. 4. Block-based data flow model.

The diagram presents a layered data-flow architecture in which physiological and mobility data are first captured by *Wearable Sensors* and collected through the *Mobile Gateway*, where the smartphone application aggregates and prepares the information for transmission. The data then pass through the *Secure API Layer*, which enables standardized and interoperable communication between system components. Next, the information is processed within *Cloud & Data Processing*, where edge/cloud computing resources and machine learning models analyze patterns and estimate health risk levels. The results are interpreted by the *Clinical Decision Platform*, which performs risk assessment and generates alerts when necessary. These alerts activate coordinated actions across *Smart Hospital*, *Emergency Services*, and *Pharmacy & Caregivers*, enabling timely intervention and follow-up.

Across the entire architecture, *Interoperability Standards* and *Security & Privacy* mechanisms ensure structured data exchange, secure communication, and protection of sensitive medical information.

6 Challenges and philosophical considerations

The proposed smart city–based architecture for the management of sarcopenic obesity faces multiple interrelated challenges across technical, clinical, organizational, and regulatory dimensions. From a technological perspective, ensuring reliable continuous monitoring requires high sensor accuracy, robustness to noise, and long-term adherence by patients, particularly older adults who may experience usability or accessibility barriers. Data acquisition and real-time transmission depend on stable, secure, and low-latency communication infrastructures, which may be unevenly available across urban environments, thereby affecting system equity and scalability. The deployment of machine learning models introduces additional challenges related to data heterogeneity, model generalizability, and algorithmic drift, especially when integrating multimodal physiological, behavioral, and contextual data streams. Clinically, balancing automated alert sensitivity with specificity is critical to avoid alert fatigue among healthcare professionals while ensuring that high-risk events are not missed. Organizational challenges include achieving interoperability among hospitals, emergency services, pharmacies, and family support systems, each of which may operate under different standards, workflows, and governance structures. Finally, compliance with data protection regulations, cybersecurity requirements, and medico-legal accountability—particularly in automated or semi-autonomous decision-making scenarios—remains a significant barrier to large-scale adoption in real-world smart city ecosystems (Kitchin, 2016; Zwitter & Helbing 2024; Wang 2024).

Beyond its technical and clinical implications, the proposed model raises important philosophical questions regarding the role of technology in human health, autonomy, and urban life. Continuous surveillance of physiological and functional parameters challenges traditional notions of privacy, shifting healthcare from episodic, consent-driven encounters toward persistent, data-centric oversight. While such monitoring promises early detection and improved outcomes, it also risks reducing individuals to quantified biological profiles, potentially reinforcing a technodeterministic view of health that prioritizes algorithmic judgment over lived experience. The integration of automated alerts and machine learning–driven risk stratification invites reflection on moral agency and responsibility: decisions affecting patient care are increasingly mediated by algorithms, raising questions about trust, transparency, and accountability when errors or biases occur. Furthermore, embedding healthcare systems within smart city infrastructures foregrounds issues of justice and inclusion, as the benefits of advanced digital health solutions may disproportionately favor populations with greater digital literacy or access to technology. Philosophically, the model calls for a human-centered approach in which technological intelligence augments—rather than replaces—clinical judgment, social support, and ethical deliberation, ensuring that the smart city evolves not merely as an efficient system, but as a socially responsible and compassionate environment for aging and vulnerable populations (de-Gracia-Soriano & Jareño-Ruiz, 2021; Ryan, 2020; Teira-Lafuente et al., 2020).

7 Conclusions

The proposed smart city architecture for identifying and managing sarcopenic obesity demonstrates the potential of digital health ecosystems to transform a traditionally reactive care model into a preventive, continuous, and coordinated one. Through the integration of biomedical sensors, secure data transmission, and real-time analysis based on machine learning, the system enables early detection of risk events and timely activation of multidisciplinary clinical responses. The eight-axis care flow demonstrates how interoperability between smart hospitals, emergency services, pharmacies, and family support networks can optimize clinical decision-making, reduce response times, and improve continuity of care. Together, this approach reinforces the viability of using smart city infrastructures as integrative platforms for managing complex, multifactorial conditions in populations entering the sarcopenic obesity stage, aligning emerging technologies with real clinical needs.

However, the implementation of this conceptual model (architecture) poses substantive challenges that transcend technical issues and require deep philosophical and ethical reflection. Limitations associated with sensor quality, communication robustness, the generalization of machine learning models, and institutional interoperability underscore the need for robust regulatory, organizational, and technological frameworks that ensure security, equity, and reliability. At the same time, continuous surveillance and the growing algorithmic mediation of clinical decision-making require a rethinking of fundamental concepts such as privacy, autonomy, responsibility, and social justice within the digital urban context. In this sense, the success of our proposal will depend not only on its technological efficiency, but also on its ability to incorporate principles of person-centered design, algorithmic transparency, and ethical governance, ensuring that the smart city functions as an environment that enhances human care, preserves patient dignity, and promotes inclusive and socially responsible healthcare.

References

An, R., Shen, J., & Xiao, Y. (2022). Applications of artificial intelligence to obesity research: Scoping review of methodologies. *Journal of Medical Internet Research, 24*(12), Article e40589. https://doi.org/10.2196/40589

Barazzoni, R., Bischoff, S. C., Boirie, Y., Busetto, L., Cederholm, T., Dicker, D., Toplak, H., Van Gossum, A., Yumuk, V., & Vettor, R. (2018). Sarcopenic obesity: Time to meet the challenge. *Obesity Facts, 11*(4), 294–305. https://doi.org/10.1159/000490361

Batty, M., Axhausen, K. W., Giannotti, F., Pozdnoukhov, A., Bazzani, A., Wachowicz, M., Ouzounis, G., & Portugali, Y. (2012). Smart cities of the future. *The European Physical Journal Special Topics, 214*(1), 481–518. https://doi.org/10.1140/epjst/e2012-01703-3

Bedrikovetski, S., Seow, W., Kroon, H. M., Traeger, L., Moore, J. W., & Sammour, T. (2022). Artificial intelligence for body composition and sarcopenia evaluation on computed tomography: A systematic review and meta-analysis. *European Journal of Radiology, 149*, Article 110218. https://doi.org/10.1016/j.ejrad.2022.110218

Bernal, M. C., Batista, E., Martínez-Ballesté, A., & Solanas, A. (2024). Artificial intelligence for the study of human ageing: A systematic literature review. *Applied Intelligence, 54*(22), 11949–11977. https://doi.org/10.1007/s10489-024-05817-z

Cauley, J. A. (2015). An overview of sarcopenic obesity. *Journal of Clinical Densitometry, 18*(4), 499–505. https://doi.org/10.1016/j.jocd.2015.04.013

Choi, K. M. (2016). Sarcopenia and sarcopenic obesity. *The Korean Journal of Internal Medicine, 31*(6), 1054–1060. https://doi.org/10.3904/kjim.2016.193

da Silva, W. M., Alvaro, A., Tomas, G. H. R. P., Afonso, R. A., Dias, K. L., & Garcia, V. C. (2013). Smart cities software architectures: A survey. In *Proceedings of the 28th Annual ACM Symposium on Applied Computing* (pp. 1722–1727). Association for Computing Machinery. https://doi.org/10.1145/2480362.2480688

de-Gracia-Soriano, P., & Jareño-Ruiz, D. (2021). Smart cities from slow philosophy. In A. Visvizi, O. Troisi, & K. Saeedi (Eds.), *Research and Innovation Forum 2021* (pp. 321–330). Springer. https://doi.org/10.1007/978-3-030-84311-3_29

Glebova, E., & Desbordes, M. (2022). Smart sports in smart cities. In D. Buhalis, B. Taheri, & R. Rahimi (Eds.), *Smart cities and tourism: Co-creating experiences, challenges and opportunities* (pp. 60–73). Goodfellow Publishers. https://doi.org/10.23912/9781915097088-4973

Gong, X.-W., Bai, S.-Y., Lei, E.-Z., Lin, L.-M., Chen, Y., & Liu, J.-Z. (2024). Study of obesity research using machine learning methods: A bibliometric and visualization analysis from 2004 to 2023. *Medicine, 103*(36), Article e39610. https://doi.org/10.1097/MD.0000000000039610

Kitchin, R. (2016). The ethics of smart cities and urban science. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 374*(2083), Article 20160115. https://doi.org/10.1098/rsta.2016.0115

Koliaki, C., Liatis, S., Dalamaga, M., & Kokkinos, A. (2019). Sarcopenic obesity: Epidemiologic evidence, pathophysiology, and therapeutic perspectives. *Current Obesity Reports, 8*(4), 458–471. https://doi.org/10.1007/s13679-019-00359-9

Lauretani, F., Russo, C. R., Bandinelli, S., Bartali, B., Cavazzini, C., Di Iorio, A., Corsi, A. M., Rantanen, T., Guralnik, J. M., & Ferrucci, L. (2003). Age-associated changes in skeletal muscles and their effect on mobility: An operational diagnosis of sarcopenia. *Journal of Applied Physiology, 95*(5), 1851–1860. https://doi.org/10.1152/japplphysiol.00246.2003

Lu, C.-W., Yang, K.-C., Chang, H.-H., Lee, L.-T., Chen, C.-Y., & Huang, K.-C. (2013). Sarcopenic obesity is closely associated with metabolic syndrome. *Obesity Research & Clinical Practice, 7*(4), e301–e307. https://doi.org/10.1016/j.orcp.2012.02.003

Onishi, S., Kuwahara, T., Tajika, M., Tanaka, T., Yamada, K., Shimizu, M., Niwa, Y., & Yamaguchi, R. (2025). Artificial intelligence for body composition assessment focusing on sarcopenia. *Scientific Reports, 15*, Article 1324. https://doi.org/10.1038/s41598-024-83401-8

Pacheco Rocha, N., Dias, A., Santinha, G., Rodrigues, M., Queirós, A., & Rodrigues, C. (2019). Smart cities and healthcare: A systematic review. *Technologies, 7*(3), Article 58. https://doi.org/10.3390/technologies7030058

Polyzos, S. A., & Margioris, A. N. (2018). Sarcopenic obesity. *Hormones, 17*(3), 321–331. https://doi.org/10.1007/s42000-018-0049-x

Přibyl, O., Pribyl, P., Lom, M., & Svítek, M. (2018). Modeling of smart cities based on ITS architecture. *IEEE Intelligent Transportation Systems Magazine, 11*(4), 28–36. https://doi.org/10.1109/MITS.2018.2876553

Ribeiro, J. C., Duarte, J. G., Gomes, G. A. O., Costa-Guarisco, L. P., de Jesus, I. T. M., Nascimento, C. M. C., Santos-Orlandi, A. A., Orlandi, F. S., Vasilceac, F. A., Zazzetta, M. S., Pott-Junior, H., & Cominetti, M. R. (2021). Associations between inflammatory markers and muscle strength in older adults according to the presence or absence of obesity. *Experimental Gerontology, 151*, Article 111409. https://doi.org/10.1016/j.exger.2021.111409

Rong, W., Xiong, Z., Cooper, D., Li, C., & Sheng, H. (2014). Smart city architecture: A technology guide for implementation and design challenges. *China Communications, 11*(3), 56–69. https://doi.org/10.1109/CC.2014.6825259

Ryan, M. (2020). The philosophy of trust in smart cities. In J. Pelegrín-Borondo, M. Arias-Oliva, K. Murata, & A. M. Lara Palma (Eds.), *Paradigm shifts in ICT ethics: Proceedings of the ETHICOMP 2020, 18th International Conference on the Ethical and Social Impacts of ICT* (pp. 36–41). Universidad de La Rioja.

Teira-Lafuente, J., Gil-González, A. B., & de Luis Reboredo, A. (2020). Philosophical approaches to smart education and smart cities. In P. Vittorini, T. Di Mascio, L. Tarantino, M. Temperini, R. Gennari, & F. De la Prieta (Eds.), *Methodologies and intelligent systems for technology enhanced learning, 10th International Conference* (pp. 239–248). Springer. https://doi.org/10.1007/978-3-030-52538-5_24

Temeljotov-Salaj, A., & Bogataj, D. (2021). Application of assistive technologies in smart cities. In *2021 29th Mediterranean Conference on Control and Automation (MED)* (pp. 657–662). IEEE. https://doi.org/10.1109/MED51440.2021.9480281

Timmins, K. A., Green, M. A., Radley, D., Morris, M. A., & Pearce, J. (2018). How has big data contributed to obesity research? A review of the literature. *International Journal of Obesity, 42*(12), 1951–1962. https://doi.org/10.1038/s41366-018-0153-7

Wang, B. (2024). Ethical reflections on the application of artificial intelligence in the construction of smart cities. *Journal of Engineering, 2024*(1), Article 8207822. https://doi.org/10.1155/2024/8207822

Zamboni, M., Mazzali, G., Fantin, F., Rossi, A., & Di Francesco, V. (2008). Sarcopenic obesity: A new category of obesity in the elderly. *Nutrition, Metabolism and Cardiovascular Diseases, 18*(5), 388–395. https://doi.org/10.1016/j.numecd.2007.10.002

Zhang, H., Wang, K., Cheng, C. Y. M., Chen, M., Lai, K. W. C., Or, C. K., Hu, Y., Vellaisamy, A. L. R., Lam, C. L. K., Xi, N., Lou, V. W. Q., & Li, W. J. (2025). Assessing sarcopenia-prone risk through daily activity of gait with AI-powered wearable IoT sensors. *IEEE Internet of Things Journal, 12*(12), 20301–20313. https://doi.org/10.1109/JIOT.2025.3543082

Zwitter, A., & Helbing, D. (2024). Ethics of smart cities and smart societies. *Ethics and Information Technology, 26*(4), Article 69. https://doi.org/10.1007/s10676-024-09803-4