Approaches to the development of information technology for ECG analysis to evaluate quality of life in smart cities*

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Abstract

The growth of innovations requires reviewing and improving approaches to assessing quality of life in smart cities. The relevance of this research is driven by the need to create a holistic and adaptive methodology that considers both technical and social aspects of citizens' lives. This paper presents an analytical review of publications on optimizing modern approaches to evaluating quality of life in smart cities using the Web of Science Core Collection scientometric database. The total number of works by year, publication types, categories, research areas, year of publication, and citation of scientific papers are shown. Publications with the highest citation rankings are analyzed. Modern approaches to assessing quality of life in smart cities are considered.

Special attention is given to the integration of healthcare systems as a key component of urban quality of life. A mathematical model of a temporal rhythm function considering extreme amplitude values of electrocardiographic signal (ECS) characteristic waves is proposed for early detection of cardiovascular pathologies. The model is represented by $T_{A_k}(m)=t_{A_k}(m)-t_{A_k}(m-1)$, where $k\in\{P,Q,R,S,T\}$, enabling analysis of temporal intervals between amplitude extrema of all characteristic ECG waves. The analysis demonstrated that the temporal rhythm functions $T_{A_P}(m)$, $T_{A_R}(m)$, and $T_{A_T}(m)$ provide more comprehensive diagnostics compared to traditional R-peak-based methods. For healthy patients, these functions show stable patterns: $T_{A_P}(m)$ ranges 0.76-0.78 s, $T_{A_R}(m)$ maintains high stability at 0.765-0.78 s, and $T_{A_T}(m)$ exhibits slight variability (0.77-0.785 s), reflecting physiological adaptability. The integration of this model into smart city infrastructure represents a significant advancement in creating comprehensive healthcare monitoring systems that enhance urban residents' quality of life.

Keywords

smart city, sustainable development, urbanization, quality of life, electrocardiographic signal modeling, cardiovascular diseases, biomedical signal analysis, artificial intelligence, temporal rhythm function, amplitude extrema

1. Introduction

In the modern urbanized world, the concept of a "smart city" is becoming increasingly popular as it aims to improve the quality of life for citizens through the effective use of technologies, infrastructure, and resource management. The problem of quality assessment in smart cities is extremely relevant as it directly affects the well-being of the population, sustainable development of urban areas, and their effective management. Quality of life assessment in such cities takes on important and special significance, as it allows monitoring the effectiveness of technology implementation, forming development strategies, attracting investments and population, and promoting social justice [1].

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Using approaches such as multichannel data integration, sustainable development indicators, Big Data analysis, digital platforms for feedback, integration of health indicators, citizen engagement, transportation system analysis, decision-making interfaces, future modeling, and artificial intelligence for automation allows evaluating the quality of life in smart cities to improve the urban environment and enhance strategies for ensuring high quality of life in smart cities [2, 3].

This paper provides an analytical review of publications on modern approaches to assessing quality of life in smart cities. The analysis was conducted using the Web of Science Core Collection scientometric database, which enables optimization of the labor intensity of searching for scientific sources according to relevant topics. The Web of Science Core Collection search system allows searching for scientific publications on specific topics or keywords, analyzing them, and processing them. The aim of the work was to review and optimize the analytical review of literature sources on modern approaches to assessing quality of life in smart cities using the Web of Science Core Collection scientometric database.

2. Review and Optimization of Modern Approaches to Assessing Quality of Life in Smart Cities

To process the relevance of publications on the review and optimization of modern approaches to assessing quality of life in smart cities in the Web of Science Core Collection scientometric database, an analytical query was formulated using the following search terms: TS=("smart city") AND (TS=("data quality") OR TS=("analysis") OR TS=("approaches") OR TS=("factors") OR TS=("assessment") OR TS=("Sustainable smart cities") OR TS=("integration of technologies") OR TS=("integrated approach") OR TS=("methodological approach") OR TS=("comprehensive approach") OR TS=("criteria") OR TS=("method") OR TS=("modern technology") OR TS=("safety") OR TS=("artificial intelligence")) AND (TS=("evaluation") OR TS=("monitoring") OR TS=("determination")) AND (TS=("observation") OR TS=("research") OR TS=("modeling") OR TS=("prognostication") OR TS=("indicators") OR TS=("standards")) AND (TS=("quality of life") OR TS=("urbanization") OR TS=("rapid diagnosis of diseases")).

The search query on this topic in the Web of Science Core Collection search platform from 2011 to 2025 found 136 scientific papers. The largest number of literature sources on this scientific topic falls within the last 8 years. Specifically, in 2018 - 10 scientific publications, 2019 - 8, 2020 - 16, 2021 - 14, 2022 - 12, 2023 - 20, 2024 - 34, 2025 - 8, indicating that research on this topic and growing interest in it worldwide are relevant and increasing every year (Fig. 1). Many scientists continue to work on this topic. This is due to the rapid development of urbanization, digital technologies, and growing demands of residents for comfort, safety, and sustainable development. These factors form a global trend toward creating cities that are more efficient, comfortable, and resilient to future challenges. Modern cities are transforming into smart cities that use innovative solutions to improve infrastructure, transportation, ecology, healthcare, and other areas of life.

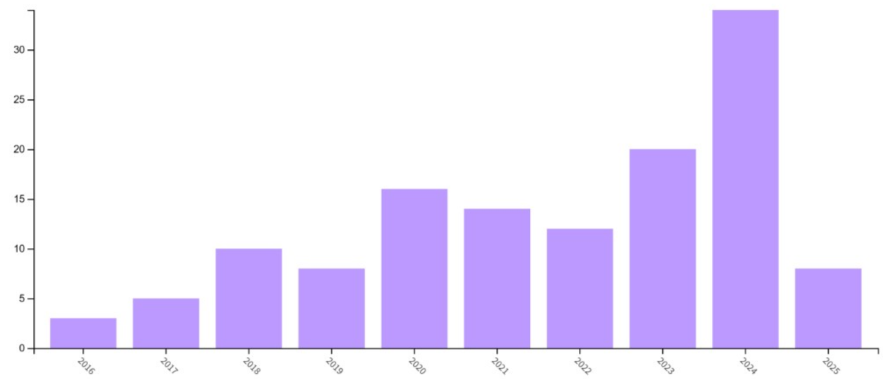


Figure 1: Search results in the Web of Science Core Collection platform (total number of papers by year).

Among scientific papers, research articles in journals predominated - 97, and Proceeding Papers - 27 (Fig. 2).

Select All	Field: Document Types	Record Count	% of 136
	Article	97	71.324%
	Proceeding Paper	27	19.853%
	Review Article	11	8.088%
	Early Access	2	1.471%
	Book Chapters	1	0.735%
	Editorial Material	1	0.735%
	Retracted Publication	1	0.735%

Analyze Data Table

Figure 2: Search results in the Web of Science Core Collection platform (types of publications).

Categories in which most articles were published: environmental sciences - 27, green sustainable science technology - 26, environmental studies - 23, urban studies - 16 (Fig. 3).

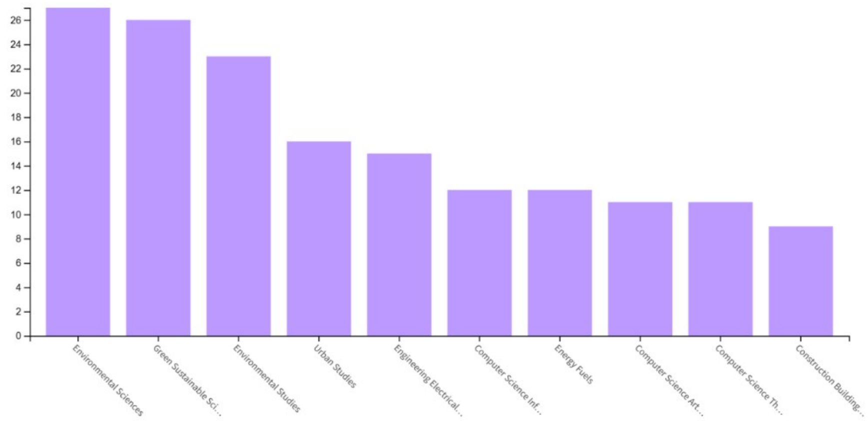


Figure 3: Search results in the Web of Science Core Collection platform (categories).

Researcher profiles in studying this problem: Hsu, Wei-Ling - 3, Xu, Haiying - 3, Yu, Lu-Gang - 3, Zhou, Shenghua - 3, Shimoda, Ryosuke - 2, Ferreira, Joao J.M. - 2 scientific papers (Fig. 4).

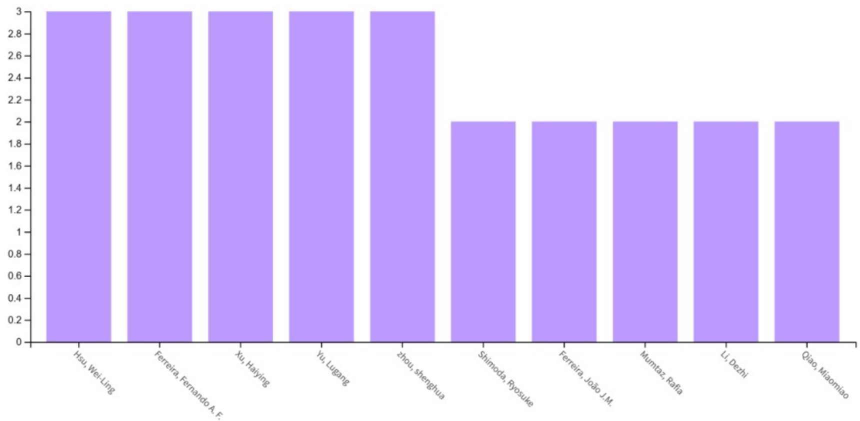


Figure 4: Search results in the Web of Science Core Collection platform (researcher profiles).

Ranking by publication titles: Sustainability - 11, Sustainable cities and society - 7, Land - 5, Smart cities - 5 scientific works (Fig. 5).

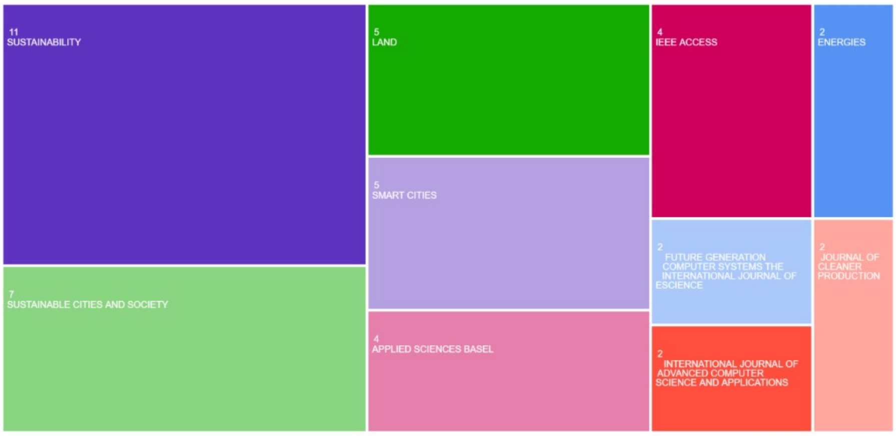


Figure 5: Search results in the Web of Science Core Collection platform (publication titles).

The number of publications is highest among scientists from the following countries: China - 34, USA - 17, India - 11, South Korea - 9 works (Fig. 6).

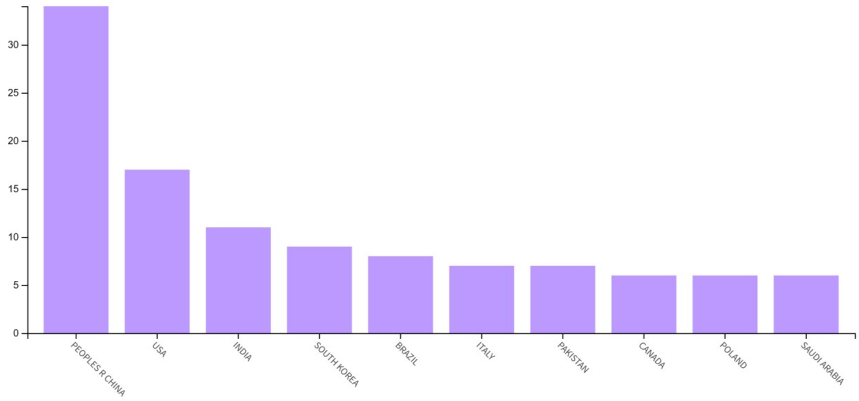


Figure 6: Search results in the Web of Science Core Collection platform (countries).

By research areas, the following stand out: environmental sciences - 37, engineering - 34, computer science - 33, scientific technology and other topics - 31, urban studies - 15 scientific papers (Fig. 7).

By the number of publications and citations from 2011 to 2025, results with the highest data indicators were obtained from 2020 to 2024 (Fig. 8). The number of publications in the last 3 years exceeds the indicators of 2020, and the number of citations is highest over the last 3 years, confirming the high scientific interest in the scientific and applied issues of modern approaches to assessing quality of life in smart cities.

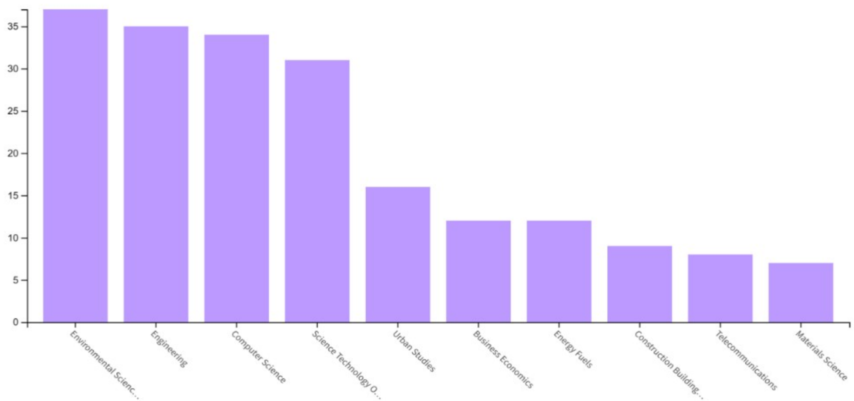


Figure 7: Search results in the Web of Science Core Collection platform (research areas).

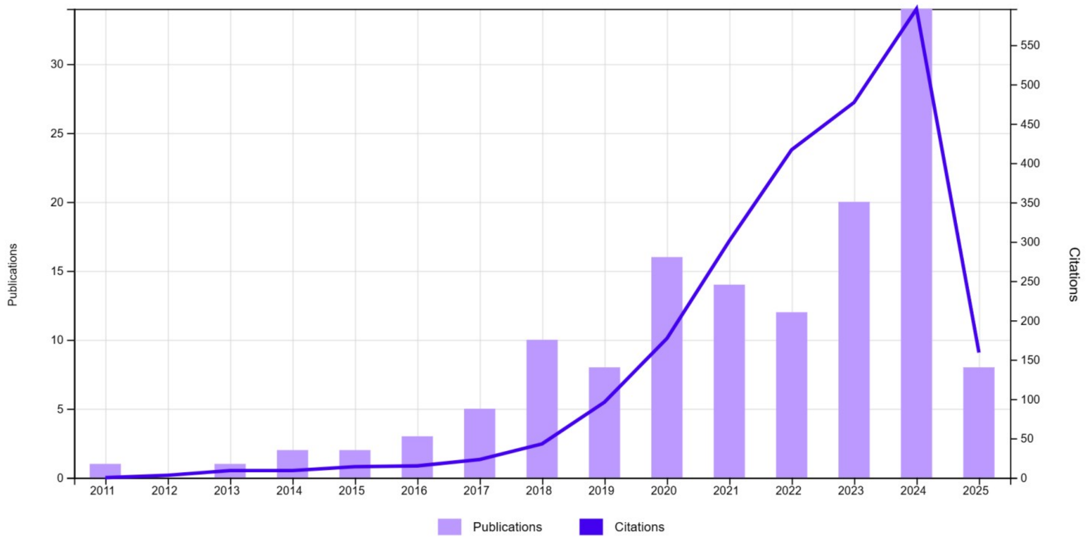


Figure 8: Search results in the Web of Science Core Collection platform (year of publication and citation).

Analyzing publications by the highest citation ranking, the following results were obtained: the greatest interest of scientists during the past year was in publications [4,5,6,7,8] - "Cyber security challenges in Smart Cities: Safety, security and privacy" with an indicator of 263, "Efficient Water Quality Prediction Using Supervised Machine Learning" - 207, "Survey on Collaborative Smart Drones and Internet of Things for Improving Smartness of Smart Cities" - 207, "A holistic evaluation of smart city performance in the context of China" - 149, "Applications of ML/DL in the management of smart cities and societies based on new trends in information technologies: A systematic literature review" with an indicator of 117. The most relevant scientific papers cover various aspects of smart city development and their impact on residents' quality of life, ecology, and management planning. Despite different methodologies, research regions, and approaches, they are united by a common goal — finding effective, adaptive, and inclusive solutions for sustainable urban development (Fig. 9).

In the paper [9], survey data collected in one of the European cities was used. Aspects related to digital services, mobility, security, environment, social inclusion, citizen participation, and urban planning were analyzed. The method of analysis was factor analysis and regression modeling.

Figure 9: Sustainable Development Goals (www.un.org/sustainabledevelopment).

Digital services positively affect the perception of quality of life, especially in healthcare, mobility, and education. Environmental aspects such as air quality and green spaces have a significant impact on life satisfaction. Key factors of quality of life in the urban environment are safety and transportation. Public participation in decision-making strengthens trust in local authorities and positively affects the evaluation of city life. The concepts of smart cities, residents' well-being, and multicriteria analysis methods are combined to assess life satisfaction in European cities [10]. The goal is to develop and apply an improved methodology for assessing the quality of life of city residents — BTOPSIS (Belief Structure Technique for Order Preference by Similarity to Ideal Solution), based on the TOPSIS method (Technique for Order Preference by Similarity to Ideal Solution), but adapted to:

- processing ordinal survey data;
- considering uncertainty (e.g., "don't know," "refusal to answer" responses);
- preserving the full range of opinions without simplifying responses.

BTOPSIS is a modification of the classic TOPSIS method, which:

- uses Belief Structure (BS) — a system of representing responses as probability distributions on the evaluation scale;
- allows storing information even from incomplete responses;
- integrates the center of gravity to account for uncertain responses;
- considers similarity of evaluations through building a similarity matrix.

Compared to other methods, such as GDM2, IF-TOPSIS, BTOPSIS better operates with fuzzy or incomplete data, avoids information loss during aggregation, and is simpler for interpretation and calculation. Researchers also compare BTOPSIS results with simple aggregated life satisfaction evaluations (QSL). They find that traditional approaches may mask subtle differences, while BTOPSIS allows identifying deeper nuances in the data, which confirms the stability and reliability of the results.

The application of artificial intelligence (AI) in urban planning to achieve smart and sustainable city development is quite appropriate. The paper analyzes which aspects of urban planning already use AI, how it can be useful, and what challenges arise for its wider implementation [11]. Four key areas of AI use are highlighted: urban data analytics and decision support, urban infrastructure management, environmental planning and risk management, monitoring and control of urban development.

Early examples of AI implementation already demonstrate real results in urban planning, and its wider implementation is possible through cooperation between authorities, IT specialists, scientists, and the public [12]. Big Data is critically necessary for effective AI functioning. Combining human and artificial intelligence is key to overcoming complex urban challenges. There is also a need for ethical standards, staff training, and algorithm transparency to avoid discrimination or errors.

Drones play a key role in data collection, surveillance, communication, environmental monitoring, disaster response, medical supply delivery, and many other functions. They can act as mobile base stations to improve communication in emergency situations or in hard-to-reach areas (Fig. 10). Collaboration of drones with IoT allows efficient collection and processing of data in real time.

The use of collaborative drones and the Internet of Things (IoT) to improve the efficiency and intelligence of smart cities is also an important aspect of the analysis [13]. It examines how drone and IoT collaboration can improve quality of life, reduce energy consumption, promote safety, support environmental initiatives, and ensure efficient infrastructure (Fig. 11). IoT devices create an infrastructure where everything — from homes to transportation — is connected to a network. Issues of energy consumption, security, and data processing are solved thanks to drones, which can collect data from IoT devices more efficiently [14].

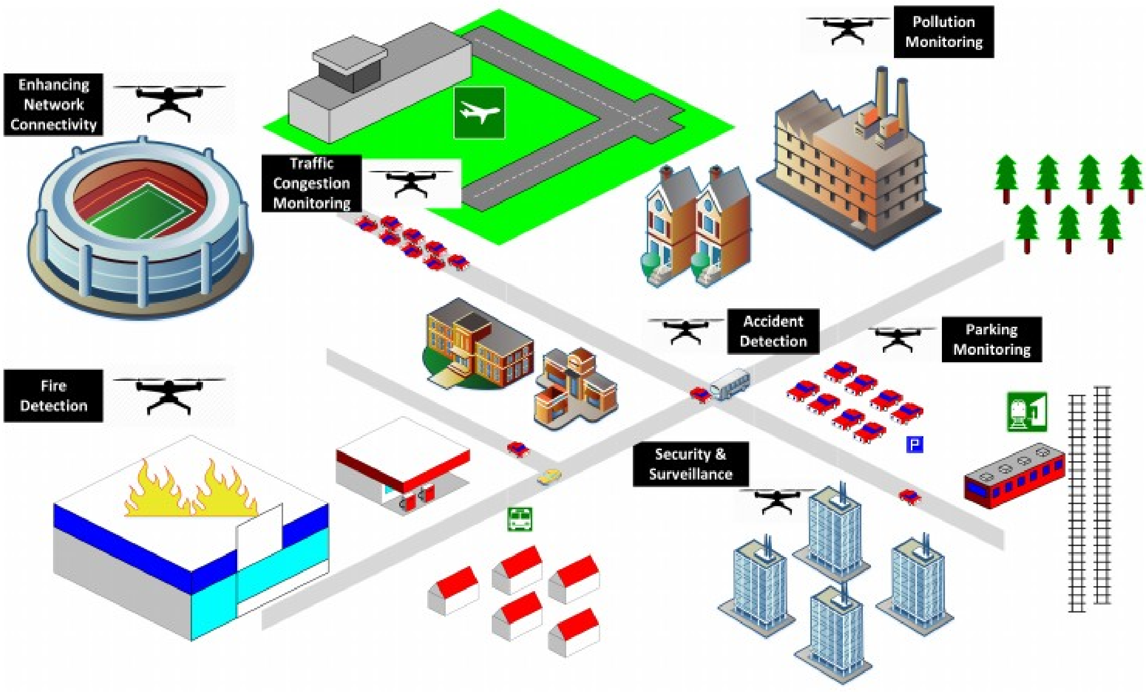


Figure 10: Collaborative drone and IoT for improving the smartness of smart cities.

In light of smart city development and growing demand for decentralized, efficient, and sustainable energy systems, a UEI (Unique Entity ID) maturity assessment model is proposed (Fig. 12), which considers the current state, benefits, and development prospects [15]. This helps cities understand what stage they are at and what steps need to be taken next.

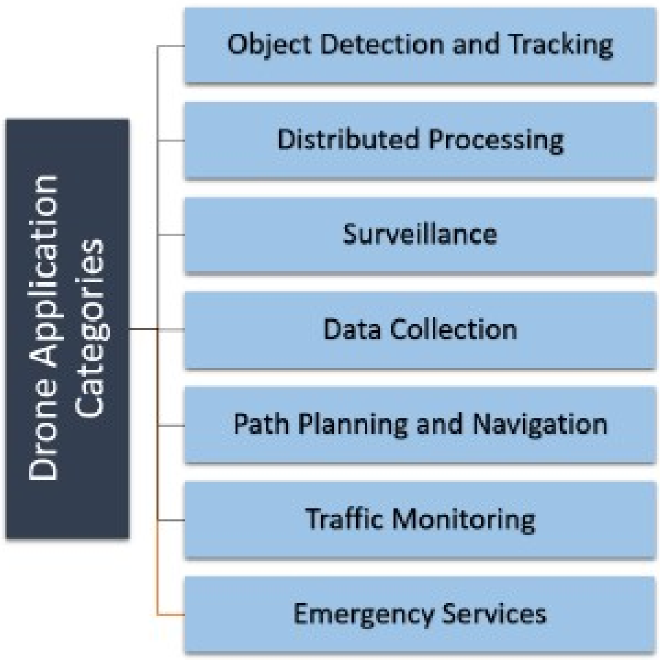


Figure 11: Drone applications categories.

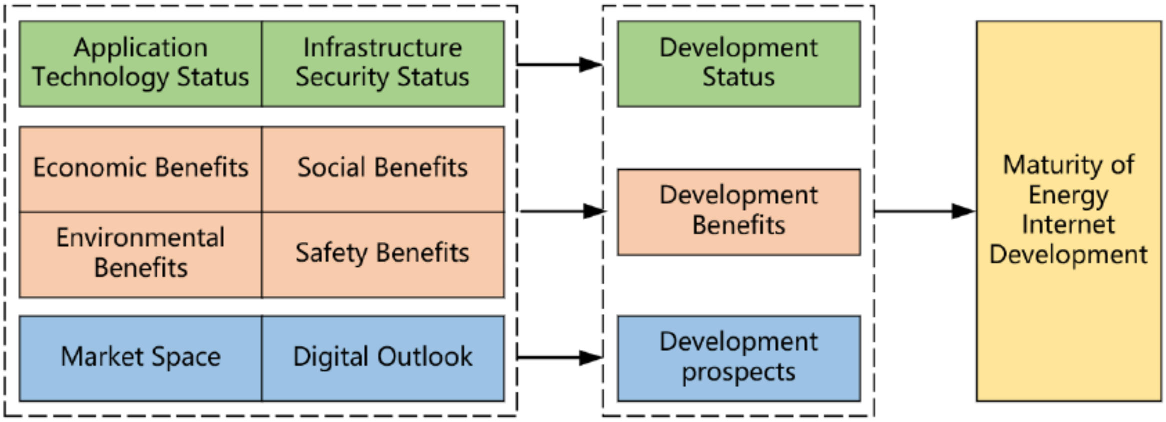


Figure 12: A hierarchical structural relationship model of the influencing factors of the development of UEI.

This model combines subjective and objective approaches:

1. Indicator system: built on three levels (primary, secondary, and tertiary indicators) — from general vision to specific technical parameters.
2. AHP (Analytic Hierarchy Process) — determines subjective weights of indicators based on expert judgment.
3. Entropy method — determines objective weights based on data variability [16].

GRA-KL-TOPSIS — an improved ranking model that uses grey relational analysis (GRA) for data normalization, KL-distance (Kullback-Leibler divergence) instead of Euclidean metrics to reduce the impact of distortions in the case of objects close to ideal, and the traditional TOPSIS model as the basis for calculating the "proximity" of a city to the ideal state.

The Unique Entity ID model has several advantages, such as:

- Improved TOPSIS model more accurately analyzes the multicriteria model.
- Combination of subjective (AHP) and objective (entropy) approaches provides a balanced assessment.
- Adaptability to different stages of city development.

A SMART-C methodology is proposed, which combines cognitive mapping and the Choquet integral for evaluating the "smartness" of cities [17]. The goal is to overcome the complexity of decision-making in this field due to the presence of numerous interconnected criteria. Urbanization, technological development, environmental challenges, and quality of life are key aspects that form the concept of smart cities. Evaluating such cities is difficult due to the multidimensionality of criteria and subjectivity of evaluations. Previously existing models have shortcomings such as lack of universal criteria, uncertainty of weights, and interrelationships between indicators.

SMART-C is an effective tool for strategic evaluation and development of smart cities, combining cognitive mapping and the Choquet integral [18] as an innovative approach to urban planning. A potential direction of development is creating software to automate evaluation. The advantages of SMART-C include integration of quantitative and qualitative criteria, process and context orientation, allowing adaptation to regional features, and stimulating stakeholder participation [19].

The world faces numerous challenges, such as environmental, economic, and social. To achieve sustainable development, effective energy management, and comfortable life, the concept of a "smart cyber city" is introduced [20]. The key elements for implementing a modern smart city are Cyber-physical systems (CPS) and the Internet of Things (IoT). The smart city concept aims to achieve smart life, smart health, smart mobility (Fig. 13).

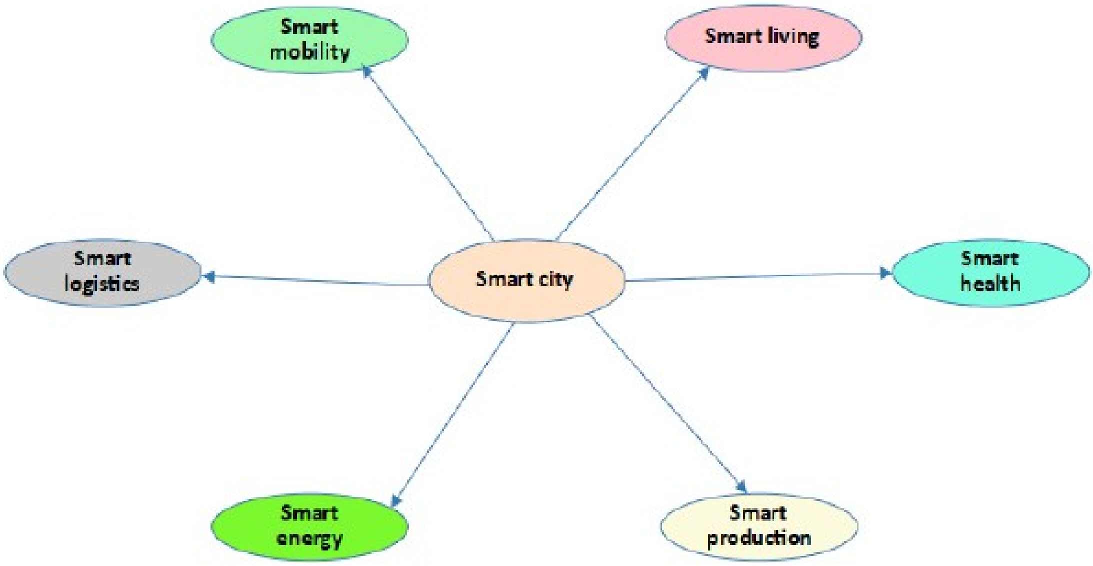


Figure 13: Smart city's goals.

A number of different technological trends in software and hardware tools can be highlighted (Fig. 14).

The foundation of smart cities is Cyber-physical systems (CPS) — a combination of physical objects and digital systems (Fig. 15) and the Internet of Things (IoT) — a network of devices for monitoring and managing processes [21, 22]. These system components play a central role in addressing challenges facing society and government.

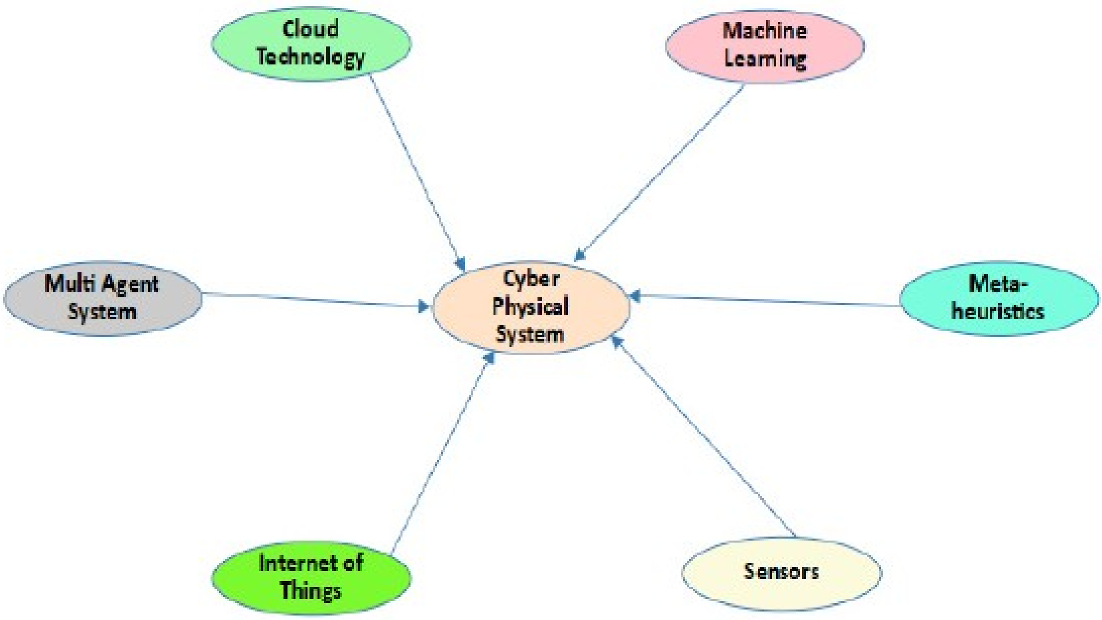


Figure 14: Smart city enabling technologies.

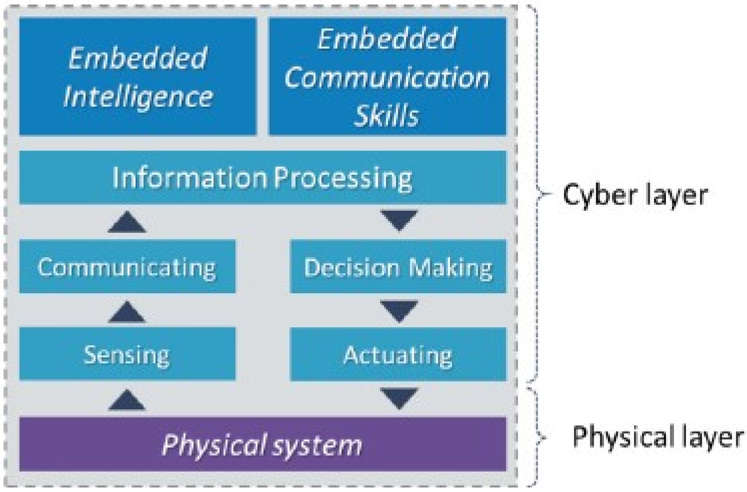


Figure 15: Graphical representation of CPS.

Smart cities are developing through the integration of advanced technologies, sensors, IoT, and information fusion. Novel human-machine interfaces based on technologies like Augmented Reality (AR) make user experiences more engaging and intuitive [23], at the same time cause a substantial increase of data volume to be processed. Machine learning (ML) and deep learning (DL) methodologies [24] play a key role in collecting, processing, and integrating data to ensure a sustainable, efficient, and safe urban environment for analyzing air quality, migration processes, water resources, security, healthcare, i.e., these methods help predict, analyze, and optimize urban processes (Fig. 16). Classification, regression, clustering, and anomaly detection are also applied to urban data.

Cybersecurity is an important component of the development of smart cities, as the growing dependence on interconnected systems, sensors and data-driven management opens up new vectors for cyber threats [25]. Protecting the integrity of data, the confidentiality of citizens' information and the availability of critical services such as transport, healthcare or energy is key. Cyber-attacks on smart networks, traffic management systems, or video surveillance networks can lead to serious disruptions in city operations or even pose a threat to public safety [26]. Machine learning methods play an important role in the cyber defence of smart cities, allowing them to automatically detect anomalies, predict possible attacks, and respond quickly to threats [27-28]. Classification, clustering, and intrusion detection algorithms are used to monitor network traffic, identify malicious activity, and improve the effectiveness of attack detection and prevention systems (IDS/IPS) [29].

Using machine learning (ML) and deep learning (DL) methods, information can be fused, which affects the development and optimization of smart cities. Through machine learning algorithms such as classification, regression, and clustering, smart cities can improve resource allocation, public safety, and overall quality of life [30, 31, 32]. However, deep learning also allows efficient processing of complex and unstructured data, which in turn contributes to more accurate prediction and deeper understanding of urban dynamics.

Integration of solar energy systems into the urban environment is key to unlocking the potential of renewable energy sources (RES) and balancing growing urban energy consumption and greenhouse gas (GHG) emissions from cities [30]. The so-called public-private-community partnership (PPP) model emphasizes inclusivity and seeks to balance technical feasibility, regulatory standards, economic considerations, and social acceptability. This approach aligns with the UN Sustainable Development Goals (SDGs), which set the direction for transforming cities into sustainable and "smart" infrastructure.

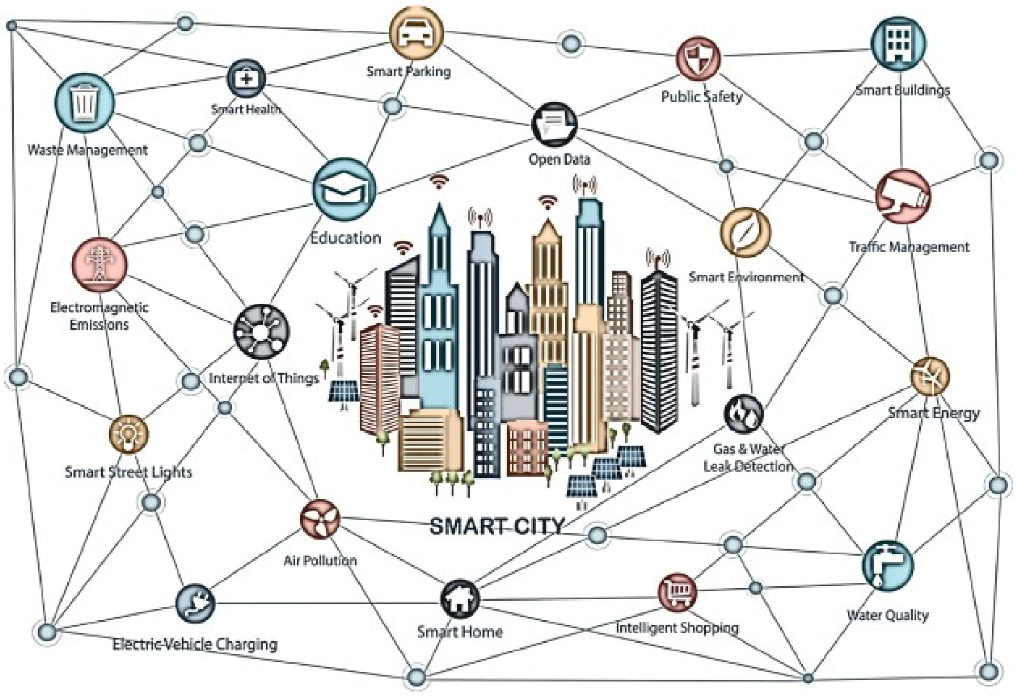


Figure 16: Bird’s-eye view of the smart city.

Focusing on solar cadastres, analyzing their development in recent years and highlighting their potential in advancing SDGs is the main direction [33]. The main goals are to harmonize terminology applied to solar web platforms, create and disseminate databases of solar cadastre examples, analyze the level of standardization achieved in these digital tools, explore the role of solar cadastres in advancing SDGs in the context of smart and sustainable cities in both high and low-income countries [34, 35]. Characteristics of solar atlases, maps, and cadastres are also outlined, allowing the formation of a classification structure for solar web platforms.

A database of solar cadastres has been created. It is not exhaustive but subject to constant updating and includes examples from around the world. This database also serves as a tool for categorizing cadastres by functionality and characteristics — such as data visualization, geometry complexity, and customization capabilities [36]. The potential contributions of solar cadastres to the development of smart and sustainable cities with a special emphasis on SDG implementation are explored. Analysis of existing cadastres allows determining how these digital tools can help form transformational pathways in technologies, policies, and behavior, supporting multi-level governance in implementing energy incentives, standards, and infrastructure to promote solar energy integration into cities.

Data from selected primary sources that address semantic interoperability issues in smart cities using relevant technologies and methods were analyzed [37]. The importance of semantic interoperability in the context of smart cities was explored; semantic technologies and tools used in smart cities to ensure semantic interoperability were identified; smart city application areas where semantic technologies are used for effective delivery of smart services were determined.

A systematic approach (Fig. 17) was used to study how scientists approach semantic interoperability technologies for smart cities and to understand the current state of affairs, using Kitchenham's recommendations [38, 39].

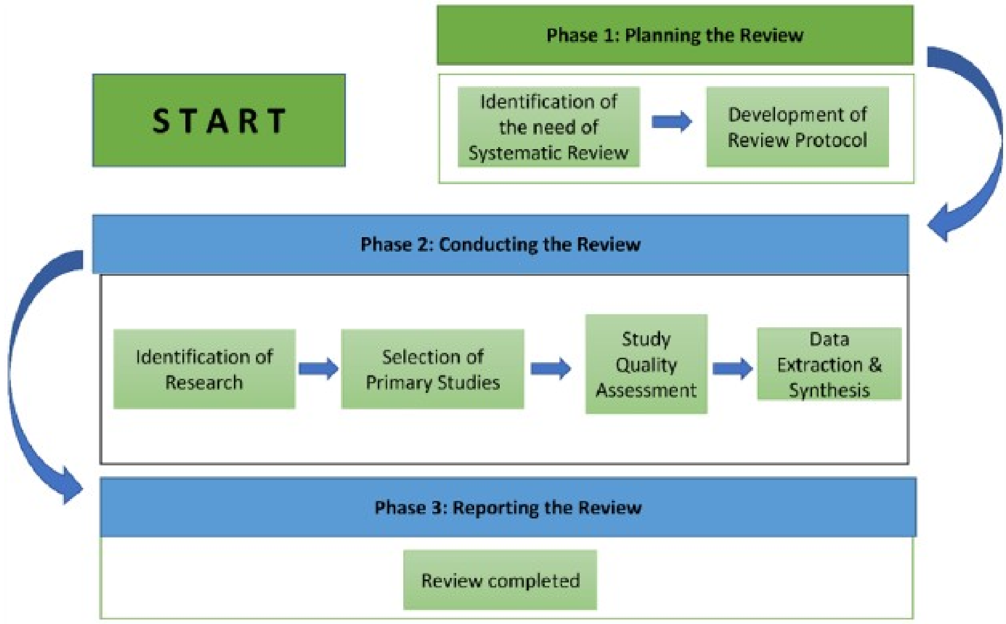


Figure 17: The phases of the SLR (systematic literature review) process.

This study systematized key aspects of semantic interoperability in smart cities, outlined its maturity levels, and proposed criteria for qualitative evaluation of solutions. Further development involves creating a quantitative evaluation mechanism, integrating the latest AI technologies, machine learning, IoT, and strengthening security and standardization of data exchange in smart city ecosystems.

Crowdsourcing in smart cities is actively developing, especially to support urban infrastructure, mobility, and environmental monitoring [40]. Crowdsourcing is an effective process for solving complex decision-making tasks [41, 42] by aggregating data, information, or opinions from groups of people, which often leads to better decisions than those made by one person and promotes diversity of opinions and independence of thinking [43, 44]. Crowdsourcing can help citizens contribute to solving urban problems, in urban planning [45, 46], and become a central pillar of joint management. Also, using the widespread presence of mobile devices accompanying users [47, 48], crowdsourcing can complement traditional sensing methods based on distributed sensor networks to obtain real conditions [44]. However, managing and processing data obtained from crowdsourcing tasks creates many inconveniences, namely the huge amount of data generated and their reliability, security of data collection processes, or regulatory standardization for transforming crowdsourcing mechanisms into effective and reliable tools [49, 50].

3. Approaches to the Development of Information Technology of ECS classification and their mathematical model of a temporal rhythm function considering extreme amplitude values of ECS characteristic waves

No less important indicators of quality of life are medical and biological parameters, as they determine the physical, mental, and social well-being of individuals. Therefore, to assess quality of life in a medical and biological context, it is necessary to consider various factors affecting human health and their ability for independent activity. The monitoring of human biosignals involves continuous or periodic measurement of physiological parameters of the organism, such as electrocardiogram (ECG), electroencephalogram (EEG), electromyogram (EMG), heart rate, respiratory rate, body temperature, sugar level, blood pressure, to assess the functional state of a person, detect deviations from the norm, and provide medical support or feedback in healthcare systems.

Modern medicine is undergoing rapid digital transformation, one of the key vectors of which is the implementation of cyber-physical systems (CPS) [51-54] (Fig. 18) — integrated complexes that combine physical components (sensors, devices) with computational elements (algorithms, software), providing automated collection, analysis, and interpretation of biomedical data in real time.

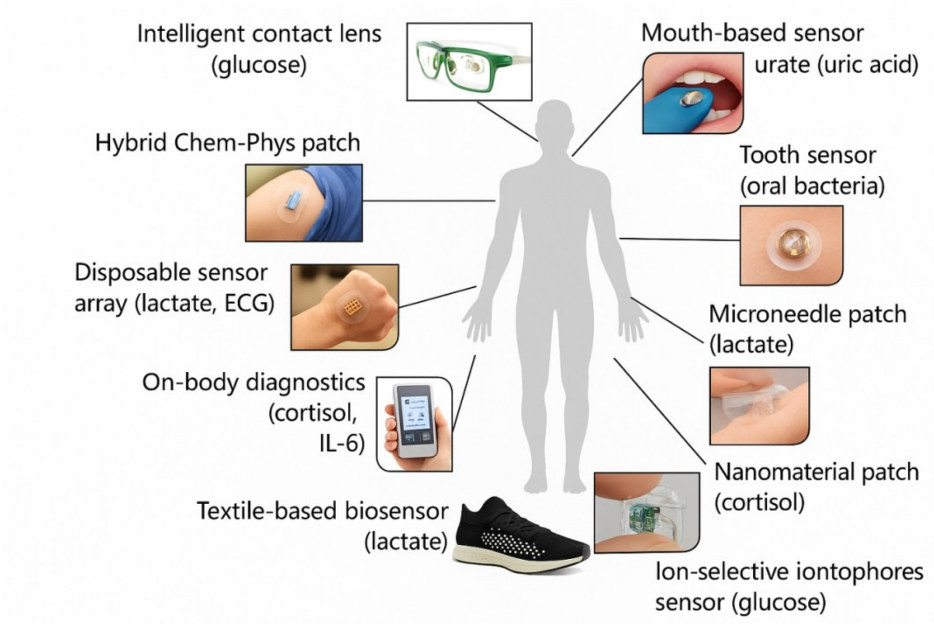


Figure 18: Cyber-physical systems of biomedical processes.

In the context of smart city concept development, creating integrated healthcare systems, which are an integral component of improving the quality of life of the urban population, takes on special significance. Among the numerous factors analyzed in this study, healthcare occupies a special place in forming the overall quality of life index in smart cities. Current trends in the development of urbanized territories involve implementing innovative methods for monitoring the health status of residents, especially for detecting cardiovascular diseases, which remain a leading cause of mortality worldwide.

The application of artificial intelligence and machine learning technologies for data analysis in smart cities allows conducting a comprehensive assessment of various aspects of urban life. Expanding this concept to healthcare, we propose integrating a system for monitoring biomedical signals, specifically, electrocardiographic signals (ECS), into the general infrastructure of a smart city. For effective analysis of ECS and detection of cardiac activity anomalies, an adequate mathematical model is needed that considers both temporal and amplitude characteristics of the signal. In this context, we propose using a model of a temporal rhythm function considering extreme amplitude values of ECS characteristic waves.

Based on the conducted analysis of publications on modeling and classification of electrocardiographic signals [55-60], we propose a model of a temporal rhythm function considering extreme amplitude values of ECS characteristic waves. The traditional temporal rhythm function provides a general characterization of the rhythmic properties of ECG signals; however, it does not account for temporal differences between various types of ECG characteristic waves, which limits the possibilities for detecting localized disturbances in cardiac electrical activity. To enhance the diagnostic value of rhythmic characteristics of individual waves, a temporal rhythm function was developed that considers the extreme amplitude values of ECG characteristic waves.

The discrete mathematical model of such a function is represented by the expression $T_{A_k}(m)$, which accounts for the amplitude peaks of ECG characteristic waves (P, Q, R, S, and T):

$$T_{A_k}(m)=t_{A_k}(m)-t_{A_k}(m-1), k\in\{P,Q,R,S,T\}, m\in Z \tag{1}$$

where: $t_{A_k}(m)$ – temporal moment of reaching the maximum of the k-type wave in the m-th cardiocycle (s);

$t_{A_k}(m-1)$ – temporal moment of reaching the maximum of the k-type wave in the previous cardiocycle (m-1) (s);

$T_{A_k}(m)$ – value of the temporal rhythm function considering extreme amplitudes, reflecting the temporal interval between peaks of k-type waves in the current m-th and previous cardiocycles;

$k\in\{P,Q,R,S,T\}$ – type of characteristic wave;

$m\in Z$ – cycle numbers.

The developed function $T_{A_k}(m)$ possesses the following properties:

1. Defined for all $m\geq 2$, since it requires the presence of a previous cycle for calculation.
2. Value domain: $T_{A_k}(m)\in(0,+\infty)$, s.

For quantitative description of the function $T_{A_k}(m)$, a statistical processing method is applied that allows calculation of the following statistical parameters:

Estimate of mathematical expectation of temporal intervals:

$$\hat{m}_{T_{A_k}}=\frac{1}{M}\sum_{m=1}^{M} T_{A_k}(m)=\frac{1}{M}\sum_{m=1}^{M}\left[t_{A_k}(m)-t_{A_k}(m-1)\right] \tag{2}$$

Estimate of variance of temporal intervals:

$$\hat{d}_{T_{A_k}}=\frac{1}{M-1}\sum_{m=1}^{M}\left[T_{A_k}(m)-\hat{m}_{T_{A_k}}\right]^2=\frac{1}{M-1}\sum_{m=1}^{M}\left[\left(t_{A_k}(m)-t_{A_k}(m-1)\right)-\hat{m}_{T_{A_k}}\right]^2 \tag{3}$$

Range of values (variational range) of temporal intervals:

$$R_{T_{A_k}}=\max_{m=1,2,\ldots,M} T_{A_k}(m)-\min_{m=1,2,\ldots,M} T_{A_k}(m) \tag{4}$$

where: M – total number of analyzed cardiocycles;

$k\in\{P,Q,R,S,T\}$ – type of characteristic wave.

In practical application, we analyzed ECS under conditions of normal cardiac function and in patient with extrasystole using the model of a temporal rhythm function considering extreme amplitude values of ECS characteristic waves. Figure 19 provides a graphical representation of a healthy patient's ECS (conditional normal) (a) and patient with extrasystole (b). The temporal rhythm function considering extreme amplitude values of ECS characteristic waves of patient (diagnosis: conditional normal) (a) and patient with extrasystole (b) $T_{A_P}(m)$ is shown in Figure 20, $T_{A_R}(m)$ in Figure 21, and $T_{A_T}(m)$ in Figure 22.

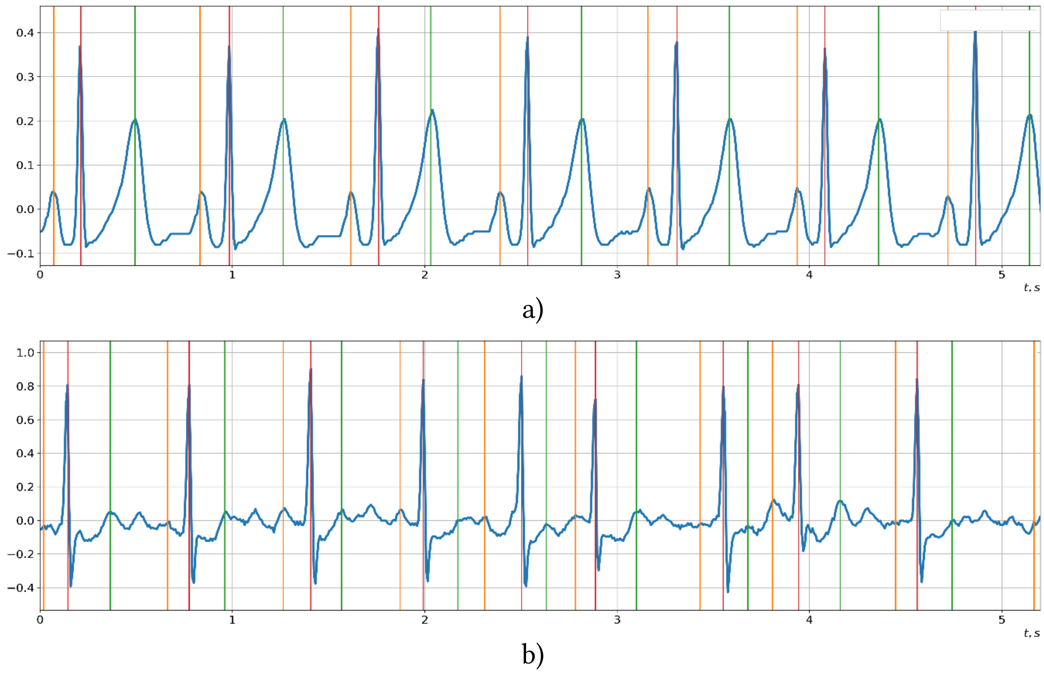


Figure 19: Graphical representation of the ECS of a healthy patient (diagnosis: conditional normal) (a) and patient with extrasystole (b).

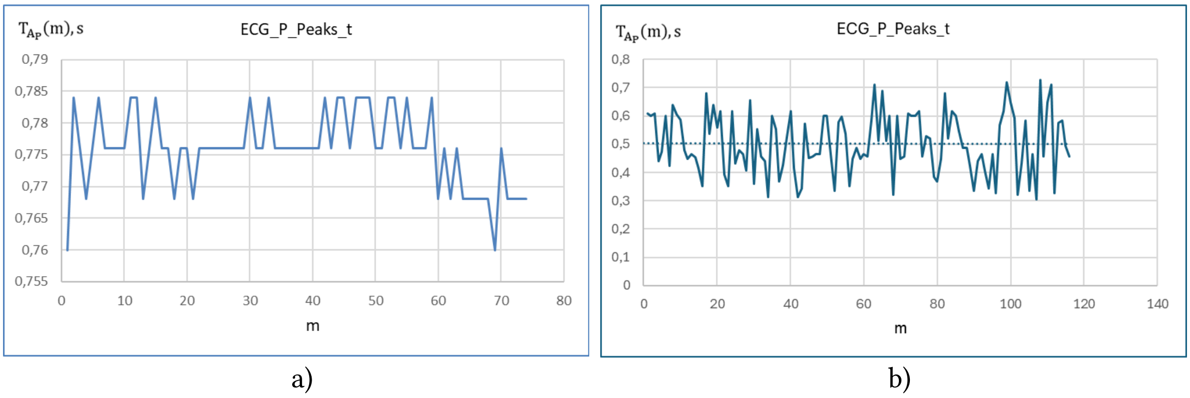


Figure 20: The temporal rhythm function considering extreme amplitude values of ECS characteristic waves of patient (diagnosis: conditional normal) (a) and patient with extrasystole (b) $T_{A_P}(m)$.

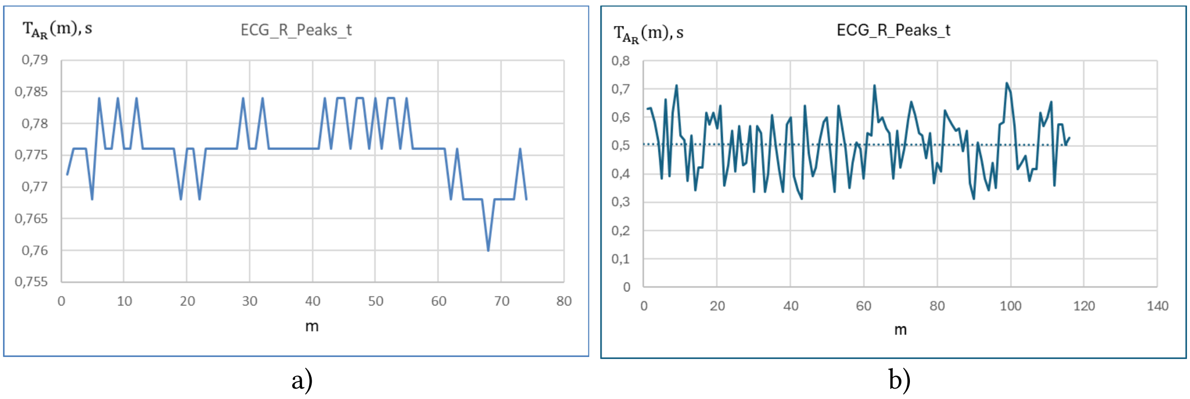
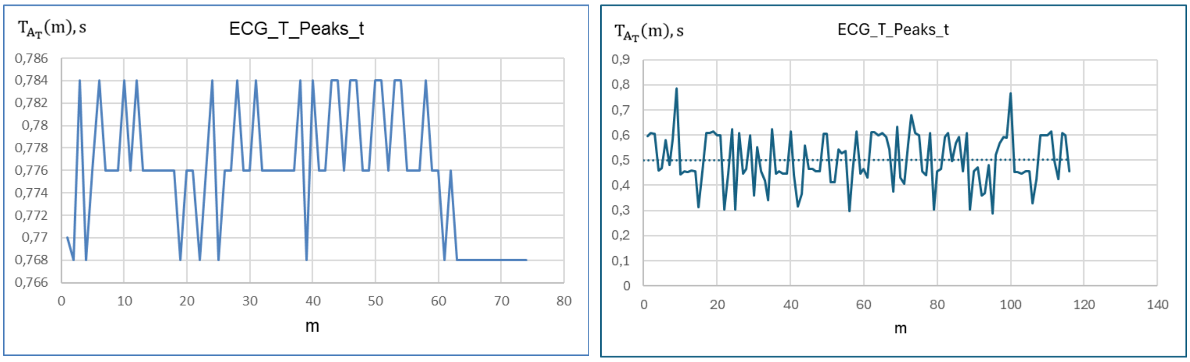


Figure 21: The temporal rhythm function considering extreme amplitude values of ECS characteristic waves of patient (diagnosis: conditional normal) (a) and patient with extrasystole (b) $T_{A_R}(m)$.



a) b)

Figure 22: The temporal rhythm function considering extreme amplitude values of ECS characteristic waves of patient (diagnosis: conditional normal) (a) and patient with extrasystole (b) $T_{A_T}(m)$.

In modern smart cities, where wireless sensor networks and edge computing technologies are already implemented, this model can be easily integrated into the existing infrastructure with minimal additional investments. Moreover, using this model for cardiac activity monitoring can be part of a broader smart health strategy, which also encompasses analyzing physical activity, air quality, and other factors affecting the cardiovascular system. Thus, the proposed model of a temporal rhythm function considering extreme amplitude values of ECS characteristic waves represents an important step toward creating integrated healthcare systems in the context of smart cities, corresponding to the general paradigm of improving the quality of life of the urban population through effective use of technologies, infrastructure, and resource management.

4. Results/Discussions

This study presents an approach to monitoring and analyzing ECS within the concept of smart cities to improve quality of life through enhancing the healthcare system. The proposed model of a temporal rhythm function considering extreme amplitude values of ECS characteristic waves demonstrates significant potential for early detection of cardiovascular pathologies.

During the study, the temporal rhythm functions $T_{A_P}(m)$, $T_{A_R}(m)$, and $T_{A_T}(m)$ corresponding to the extreme amplitude values of characteristic P, R, and T peaks of the electrocardiogram were analyzed. For healthy patients (conditional norm), these functions demonstrate stable, predictable patterns with minimal deviations: for $T_{A_P}(m)$, a stable range of values 0.76-0.78 s with minor fluctuations is observed; for $T_{A_R}(m)$, high stability in the range of 0.765-0.78 s is characteristic; for $T_{A_T}(m)$, slightly greater variability (0.77-0.785 s) is detected, reflecting the physiological adaptability of the repolarization phase based on T-wave amplitude extrema.

The analysis showed that comprehensive consideration of temporal intervals between extreme amplitude values of all three wave types provides more reliable diagnostics than using only R-peaks, which is traditional in many monitoring systems. In particular, changes in the temporal rhythm function $T_{A_P}(m)$ based on P-wave amplitude extrema may indicate atrial pathologies before changes in R-peak patterns appear.

Conclusion

As a result of the conducted research, a comprehensive analysis of modern approaches to assessing quality of life in smart cities based on the Web of Science Core Collection scientometric database was performed. The obtained data confirm the growing scientific interest in this topic, which is due to the relevance of the problem in conditions of rapid urbanization, technological progress, and growing demands of residents for a quality urban environment.

Quantitative analysis of publications showed a dynamic growth in the number of studies, especially in recent years, indicating a global trend toward finding effective solutions in the fields of urban planning, digitalization, and sustainable development. The thematic diversity of research covers ecology, transportation, digital services, social inclusion, security, citizen participation, and technologies based on artificial intelligence and big data.

The paper also examines leading methodological approaches to evaluating quality of life in smart cities, in particular: BTOPSIS, SMART-C, integration of drones with IoT, analytic hierarchy approach combined with entropy methods, and the use of artificial intelligence tools. These approaches allow comprehensive coverage of both quantitative and qualitative indicators, account for uncertainty, and provide adaptability to regional conditions.

A particularly significant result of the study was the development of an innovative model of a temporal rhythm function considering extreme amplitude values of electrocardiographic signals. This model, defined as $T_{A_k}(m)=t_{A_k}(m)-t_{A_k}(m-1)$, where $k\in\{P,Q,R,S,T\}$, makes a significant contribution to improving the assessment of quality of life in smart cities through the prism of healthcare, which is an integral component of the overall quality of life index.

The proposed model of temporal rhythm function considering extreme amplitude values is characterized by the following advantages:

1. Comprehensiveness of analysis: unlike traditional approaches that focus mainly on R-R intervals, the developed model analyzes temporal intervals between extreme amplitude values of all characteristic ECS peaks (P, Q, R, S, T), providing a multidimensional analysis of cardiac activity.
2. High diagnostic accuracy: considering extreme amplitude values as temporal markers allows detecting pathological changes at early stages when they are not yet manifested in traditional indicators. The focus on amplitude extrema provides more robust and reliable detection of cardiac abnormalities.
3. Resource efficiency: the model does not require significant computational power since identifying extreme values is computationally simple, making it suitable for integration into wearable devices and integrated monitoring systems in the urban environment.
4. Adaptability: the proposed temporal rhythm function easily adapts to individual features of a specific person's ECS, as extreme amplitude values naturally account for individual variations in signal morphology.

Combining the proposed model with other components of a smart city (IoT, big data, artificial intelligence) creates a synergistic effect, allowing analysis of the impact of various factors of the urban environment (air quality, noise level, transport load) on the cardiovascular system of residents. The focus on extreme values makes the model particularly suitable for real-time processing in smart city infrastructure.

The conducted research allows forming foundations for the further development of interactive tools for evaluating the "smartness" of cities, such as dashboards or decision support systems. In particular, a promising direction is the development of an evaluation model adapted to Ukrainian realities, which would consider local social, economic, and technological features, as well as the involvement of stakeholders in forming a vision of the smart city of the future.

Thus, the article makes a significant contribution to systematizing existing approaches, highlighting the most effective methodologies, and forming foundations for further research and practical implementation of tools for assessing quality of life in the context of smart cities. The proposed model of a temporal rhythm function considering extreme amplitude values of ECS characteristic waves is an important step toward creating comprehensive healthcare systems as an integral component of the smart cities of the future, aimed at ensuring a high quality of life for the urban population.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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