

Modeling Future Cities Driven by Generative Artificial Intelligence Systems

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Abstract

The article presents city modeling processes based on generative artificial intelligence systems. A Case Based Reasoning (CBR) method is proposed to formalize the modeling processes. The proposal to use this method stems from the author's experience in formalizing knowledge about urban development and analyzing development cases. It is proposed to conduct four research experiments on urban development processes, which will be recorded in case knowledge bases. The generalization of the cases using the CBR method will form the basis for forecasting urban development.

Keywords: cities AI, digital cities, cities of the future, generative artificial intelligence models, Case-Based Reasoning method, governance in RAG

1. Introduction

The development of generative artificial intelligence systems will completely change the picture of future cities, where the processes of the town and its entities will require implementing these systems (Lombardi et al., 2011, Makiela et al., 2022). The question that arises here is whether existing information technologies will only be replaced by generative artificial intelligence systems or whether generative artificial intelligence systems will

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change the behavior of entities and their processes in city development (Europeansmartcities 3.0, 2014, Rane, 2023). An analysis of the literature shows how widely the issue of generative artificial intelligence and especially the use of ChatGPT is currently being discussed (Quan, 2022, Rane, 2023). Many works point out their usefulness from the point of view of the questions posed (Leake et al., 2023). If we assume that in the future cities will develop based on the use of generative artificial intelligence systems, the question arises: how these systems should be created, what resources they should use, and, above all, how generative artificial intelligence systems should be used (Rane, 2023). They can be an alternative to existing information systems, but they can also significantly support the decision-support systems that are so important for cities (Orłowski, 2019, Orłowski, 2020)

To fill this gap, the article singles out four of the areas of the city's functioning, assuming that for each of these areas, research experiments will be carried out with the aim of actual implementation of processes in the town and then preparing descriptions of these experiments in knowledge bases using the selected CBR method (Badura et al., 2007). The result of this work is to be four main models and three auxiliary models.

Main models:

- A model for the development of smart buildings based on research labs and development scenarios.
- A model for managing the development of cross-sector partnerships in innovative grid data acquisition processes.
- A model for managing the development of digital medical data supported by generative artificial intelligence mechanisms.
- A model for diagnosing and predicting the condition of Emergency Department patients based on air quality data analysis.

Support models:

- Models of generative artificial intelligence systems for cities.
- A model for component commercialization of theses.
- LLM RAG systems governance in the development of future cities

Table 1. Shows the processes of building these models. The construction processes have been divided into stages, and the fields in which experiments will be conducted have been identified. The main process of building knowledge models for generative artificial intelligence is also defined, as well as a supporting process to carry out a series of theses, the structure of which will include commercialization components.

Table 1. Development processes of future cities using generative artificial intelligence

	Stage I – Development of the concept of the research being conducted	Stage II – Assumptions for the construction of the test site	Stage III – Construction of the test bed	Stage IV – Research experiments	Stage V – Description of experiments for powering knowledge models
Areas of urban development	1. A model for the development of intelligent buildings based on research laboratories and their development scenarios 2. A model for developing cross-sector partnerships in innovative grid data acquisition processes. 3. A model for managing the development of digital medical data supported by generative artificial intelligence mechanisms. 4. A model for diagnosing and predicting the condition of Emergency Department patients based on air quality data analysis.	Development of the research design within the adopted five stages	How to build a research position and how to develop it	How to situate stations and how to implement research processes	Selection of research scenarios
					Construction of knowledge bases based on conducted research with the involvement of students and their verification from the point of view of CBR templates

Main process	Models of generative artificial intelligence systems for cities	Development of the research design within the adopted five stages	How to implement generative artificial intelligence models and how to integrate them with the CBR method	Building a knowledge base generation environment for generative artificial intelligence	Selection of research scenarios	Construction of knowledge bases based on conducted research with the involvement of students and their verification from the point of view of CBR templates
	Model of component commercialization of thesis	Development of the research design within the adopted five stages	How to select theses and how to describe them for generative artificial intelligence models	Selection of scientific research units for commercialization of scientific research and implementation of the evaluation process	Selection of research scenarios	Construction of knowledge bases based on conducted research with the involvement of students and their verification from the point of view of CBR templates

The choice of urban development areas as well as the method of knowledge formalization stems from long-term cooperation in Smart Cities development as well as the authors' experience with knowledge formalization using the CBR method (An Artificial Intelligence Based Automated Case-Based Reasoning (CBR), 2024, Badura et al., 2007). This is a frequently used method of formalizing knowledge in management; using four processes: Retrieval, Reuse, Revise, and Retain, we generalize knowledge about a domain. Each new case feeds into the existing knowledge base, which, from the point of view of intelligent systems, is a key element of the systems learning process (Guerrero et al., 2022)

. Therefore, it was decided that the article should be divided into six main parts. It was decided to describe four processes of city operation based on the analysis of real cases of city development described in theses with a strong commercialization aspect. On this basis, knowledge bases will be built to feed a generative artificial intelligence system for Smart Cities. It is assumed that each of these four processes (based on the case study) is described using the CBR method. Then, the creation of knowledge bases will include the following processes: defining the problem and collecting and representing cases with their indexing, defining probability measures, and, based on this, finding and adapting cases for generating predictions.

Other knowledge formalization methods such as Natural Language Processing (NLP), Topic Modeling, Word Vectorization, Classification Algorithms, Automatic Summarization, Ontologies and Knowledge Graphs, Automatic Content Generation, Named Entity Recognition (NER), and Pattern Recognition were also considered. However, it has been assumed that CBR is an artificial intelligence method that is not necessarily explicitly assigned to one particular group of methods (Schoenborn et al., 2021), Voskoglou, 2023). Rather, CBR is considered a problem-solving approach and is most often assigned to Pattern Recognition (Compendium of Neurosymbolic Artificial Intelligence - Google Books, 2024, Sourati et al., 2023)

This approach makes it possible to integrate the city's processes, point out those whose chance of realization is greatest, and, at the same time, show how stored knowledge bases can be used in systems such as ChatGPT or generative j artificial intelligence system production environments such as Watson (Schoenborn et al., 2021, Zheng, 2021). It also seems that this article aims to integrate the research team, which is important for complex systems. After all, if we treat that the future city requires multifaceted, multicriteria, and multidimensional analysis, then such a six-member research group enables a multidimensional perception of the city.

To build these models, it is necessary to refer to the analysis of the state and literature. Therefore, the starting point was representative works considering these four research areas. It was assumed that three main works were selected for each of these four areas, indicating how cities function in these areas. This approach can be the basis for building the proposed models.

The first to consider the model of development of smart buildings and three works were taken into account here (Barroso et al., 2023, Khatibi, 2023, Rodríguez-Gallego et al., 2023). In [3, Rodríguez-Gallego et al., 2023) analyzed the behavior of residents as a basis for obtaining data to use this data and then to create research environments. It indicated the possibilities of creating research environments and data transfer structures as part

of joint work. The work (Barroso et al., 2023) indicated the possibilities of creating smart campuses in order to create smart measurement networks within these campuses. The work (Khatibi, 2023) indicated the possibilities of creating measurement networks using data from building elements such as smart windows.

In the case of building the second model of managing the development of intersectoral partnerships, the works (Sadabadi et al., 2024, Susha et al., 2023, Yusof et al., 2023) were considered. In (Yusof et al., 2023), attention was drawn to the need to monitor the functioning of such partnerships in real time. It was also pointed out to the need to share information through cooperation with government agencies and international organizations. It was also suggested to create platforms to share information in real time about threats and vulnerabilities. In (Susha et al., 2023) it was indicated that the basis for the functioning of partnerships is sharing data. Examples of three intersectoral partnerships were presented and six cases of their behavior were analyzed. Driving factors and key mechanisms of cooperation were indicated. Article (Sadabadi et al., 2024) showed the importance of social entrepreneurship in promoting links between the public and private sectors. The role of social entrepreneurship was examined and it was shown how it relates to the functioning of social networks.

In the case of the third model, the state of knowledge in this area was analyzed based on representative works (Moulaei et al., 2024, Nova, 2023, Reddy, 2024). In (Reddy, 2024) it was shown how generative artificial intelligence can be used in healthcare. A comprehensive review was carried out, allowing the authors to analyze the proposed model in the context of existing models. It indicated the applications of generative artificial intelligence in the field of diagnostics, treatment and research, as well as change management. In (Moulaei et al., 2024), similarly to the previous one, a review of literature on the possibilities of using generative artificial intelligence in healthcare was carried out. It indicated the importance of generative artificial intelligence in such areas as offering information about health status by asking appropriate questions, diagnosing and predicting diseases, and combining the benefits and problems associated with generative artificial intelligence. In turn, in (Nova, 2023), the importance of medical documentation treated as an automatic summary of the conversation, simplifying complex medical language for the patient, providing personalized recommendations for medical care, and using smartwatches was shown. The technical framework for using generative AI to analyze this data and suggest behaviors was presented. The analyzed processes concerned both speech recognition and natural language processing, as well as the recognition of medical entities and contextual understanding.

In the case of the fourth model, representative works focused on a model for diagnosing and forecasting the condition of patients using air quality data (Gafni-Pappas et al., 2023, Palus et al., 2023, Surit et al., 2023). In (Ravindra et al., 2023) a study was presented to analyze the impact of air pollution on patient visits to hospitals due to respiratory diseases. Data from 2018-2021 was analyzed, and machine learning algorithms were used to allow for such forecasts. The data was divided randomly, and the collected test and training data sets were processed using generative AI. In turn, (Gafni-Pappas et al., 2023, Surit et al., 2023) the importance of generative AI for data analysis and the relationship between air quality and morbidity was already shown. Aspects related to data privacy and the possibility of using them to process complex data were analyzed. Technology acceptance models were analyzed to analyze the possibility of using them to analyze medical data. The potential of generative artificial intelligence in diagnostics and treatment billing was pointed out.

This article is also an example of how a group of eight potential doctoral students demonstrates how the processes between the city and that scientific research unit can be improved by pursuing doctoral work at a scientific research unit. It also implements these processes for the benefit of the city and, at the same time, holistically sees the importance of these processes from the point of view of generative artificial intelligence systems. Indeed, if we assume that these four cases will be the pilot version of the construction of knowledge bases for generative artificial intelligence systems, then each subsequent new case will be created using the method adopted in this article. Thus, the construction of a generative artificial intelligence system, regardless of whether it will be a city autonomous system or what, perhaps at this stage of the preparation of the article, seems most likely a decision support system, will be based on city-verified methods of knowledge collection.

2. Materials and methods

In this part of the article, we will present seven concepts and development processes of modeling for cities using genetic artificial intelligence. The sections will present concepts and models divided into main and supporting models, as shown in Table 1.

2.1. The concept of building a model for the development of Smart Buildings based on research laboratories and their development scenarios

In constructing the knowledge base model concept, a solution was used in which the construction of the model of the operation of these laboratories will be incremental. It was assumed that to construct knowledge bases, we would use knowledge about the functioning of small research laboratories operating at companies producing building materials for intelligent buildings. The model was built based on experience from the following articles (Barroso et al., 2023, Khatibi, 2023, Rodríguez-Gallego et al., 2023). It becomes necessary in this case to analyze the functioning of these laboratories their place in the network of both design and manufacturing of building materials, and their relationship with large research laboratories.

Another important consideration also seems to be whether we will consider only laboratories focusing on selected smart building functionalities such as energy savings or types of building materials. It is worth considering the possibility of integrating diverse laboratories in terms of their form of operation. The analysis of the state of the literature presented in publications (Etzkowitz et al., 2000, Europeansmartcities 3.0, 2014) shows that it will become necessary to consider building a model that is based on both an incremental approach and also takes into account the fact that we integrate laboratories regardless of the types of their functionality. This means that we will use in the construction of the network those existing research laboratories with high integration potential and those small ones without integration potential for the design, construction, and maintenance of smart buildings. Therefore, at this stage, it seems expedient to analyze existing laboratories to isolate those that will form the basis for building a model of cooperation and then analyze the status of this cooperation.

At this stage of work, three types of laboratories can be distinguished:

- Testing construction materials,
- Woodworkers examining joinery,
- Investigating the energy efficiency of buildings

Before starting the modeling processes (stage 1, fig.1), existing research laboratories were analyzed, mostly organized at ample research and development units, to a much lesser extent at companies producing materials for smart buildings. Seven of the research laboratories are laboratories that may represent the potential for collaboration at some stage of the development of the model proposed in the paper:

- Team of Environmental Research Laboratories of the Ship Technology Center S.A. in Gdansk.
- Polskie Centrum Badań i Certyfikacji S.A. in Warsaw.
- Laboratory of the Department of Construction and Environmental Engineering of the West Pomeranian University of Technology in Szczecin.
- Building Materials Research Laboratory Ltd. in Ostroda.
- Lukaszewicz - WIT Lukaszewicz - WIT Warsaw.
- MOBILE Laboratory of Construction Technology Ltd. Walbrzych.
- Building materials laboratory opolska polytechnic.

We have defined the types of laboratories subject to integration for smart buildings (De Silva et al., 2012, Ding et al., 2011). We have established the nature of the model construction that will support the integration of these laboratories. What will be the purpose of integrated laboratories working for smart buildings? Will it be to study many different functionalities of a smart building. Or is it to isolate one that will integrate the laboratories on the one hand and, on the other hand, will be the most important from the point of view of construction, development, and maintenance of smart buildings? To answer this question, a relevant inquiry was made to ChatGPT: Which of the processes, design, construction, or operation, can be the integrator of the laboratories that study intelligent buildings?

Design integrators typically have a wide range of responsibilities, including planning, designing and coordinating various aspects of construction, including technical infrastructure, building control systems, energy systems, etc. In the case of smart buildings, design integrators must be able to incorporate a variety of technologies, sensors, energy management systems, and other innovations to create integrated solutions that meet customer requirements and are effective in increasing energy efficiency and comfort for building occupants. A design integrator can, therefore work to harmonize the various research labs, ensuring that their work is coordinated and integrated to achieve optimal results in a smart building

According to table 1, the processes of building knowledge bases will concert at stage two of the assumptions for building a test bed. This stage aims to integrate research laboratories in the area of smart building design. This

integration will occur in three key areas - building materials, carpentry, and energy efficiency research - and may include various aspects. This integration will include data sharing, joint research, collaboration to develop innovative solutions, and coordination of activities to achieve better results (stage 3). Suggestions on how to integrate laboratories in each of these areas will be presented below:

Building Materials:

- Data exchange: Testing laboratories can exchange information on new building materials, their properties, performance, and applications. This may include sharing test results, material specifications, and data on strength, thermal insulation, sound insulation, etc.
- Joint research projects: Laboratories can collaborate on research into new building materials by joining projects funded by various sources, such as research grants or industry funds.
- Testing and evaluation: laboratories can cooperate in testing new materials for strength, weather resistance, thermal insulation, sound absorption, etc.

Woodwork:

- Standardization and harmonization: Laboratories can jointly develop standards for joinery, which will make it easier to compare test results and ensure a uniform approach to evaluating the performance of different products.
- Performance testing: Laboratories can conduct tests on various types of woodwork, such as windows, doors and facades, to evaluate their thermal insulation, air permeability, resistance to rain and wind, or exterior noise.
- Innovation research: Working together, the labs can research innovative woodwork solutions, such as smart windows and natural light management systems.

Building energy efficiency study (stage 4):

- Modeling and simulations: Laboratories can conduct advanced computer simulations on building energy efficiency, including analysis of heat flow and energy consumption or assessing the impact of various ventilation and air conditioning systems on energy consumption.
- Field measurements: Working together, laboratories can conduct measurements in actual buildings to assess their energy efficiency and identify potential areas of improvement.
- Research on energy management systems: Collaborative research on advanced building energy management systems can lead to more efficient solutions that reduce energy consumption and operating costs.
- All these activities can be coordinated and integrated by relevant institutions, such as research centers, universities, industry associations, or government institutions, to ensure synergistic effects and maximize the impact of research on the development of smart buildings.

At this stage of the article's preparation, it is difficult to determine the fifth stage of the research, assuming that they will be derived from the development of stage two, whose processes have been described above.

Based on the analysis of the state of existing testing laboratories, the question then becomes, where should smart home testing laboratories be placed, and how should they be integrated? The answer to this question would probably be provided by analyzing the financial affluence of residents in different areas of the country. Smart home development has a better chance in areas close to technology centers. Near universities, especially those closely related to materials engineering, computer science, and electronics. It is also important to locate them in areas with access to a pool of skilled workers and smart home specialists surrounded by a public interested in technology development.

In turn, the basis for concluding the possibility of integrating research laboratories is the chapter related to the assumptions for building modeling processes and the modeling processes themselves. It is tough at this stage of research concept construction to isolate the integration processes and the functionalities that form the basis for integration. Therefore, in the first part, the assumptions for the construction of the model, on the one hand, the state of the literature was analyzed, but on the other hand, suggestions for ChatGPT were also used.

Both the suggestions from ChatGPT and the modeling processes indicate that the most important thing, however, is an expert assessment by those who deal with research laboratories daily work with them, and indicate which areas could be the basis for integration (ChatGPT and Similar Generative Artificial Intelligence (AI) for Building and Construction Industry, 2024). Therefore, based on expert analysis, three such areas were identified and presented in the modeling processes. The subsection presenting the modeling processes for the three different functionalities shows, on the one hand, how diverse the approach should be and, on the other hand, perhaps indicates that it is becoming necessary to analyze the potential of the research laboratory selected for further work to start the integration processes.

2.2. The concept of building a management model for the development of cross-sector partnerships in the processes of data acquisition from smart metering networks

The purpose of this part of the article is to present a proposal for a model for managing the development of cross-sector partnerships in the context of smart metering data acquisition. The main objectives include the analysis of the key factors determining the effective development of cross-sector partnerships, the identification of barriers and challenges to building and maintaining partnerships in this area, the development of a proposal for a management model for the development of partnerships taking into account the specifics of data acquisition from smart metering networks, and the evaluation of the proposed model based on case studies. To present this, it becomes necessary to analyze the determinants of developing these partnerships (Broström, 2011, Kempton et al., 2021).

The increase in demand for smart technologies is determined by the desire to reduce the cost of maintaining cities and increase the comfort of their residents. Building smart cities is a partnership process that requires adapting the decision-making instruments used to the needs and competencies of local communities. Advanced technologies working together with social actions support the cooperation of local authorities with residents and contribute to creating a mechanism for developing social capital (Etzkowitz et al., 2008, Makiela et al., 2022).

This is well understood by the residents and authorities of the Danish city of Aarhus, a leader in the so-called "Scandinavian Third Way" in developing cross-sector partnerships. This Danish town took second place in the 2014 European Smart Cities ranking. (in the category of cities with a population of 100,000 to 500,000) (Europeansmartcities 3.0, 2014, Farinha, 2012). It is home to numerous startups, research and development departments of leading technology companies (Google, Uber and eBay) populated, among others, by a group of more than 20,000 professionals in the Internet of Things, Big Data, Data Science and similar fields or 40,000 students (Baraniewicz-Kotasińska, 2022).

Thanks to a grassroots initiative by the Alexander Institute (a non-profit organization) and Aarhus University, the idea of Smart Aarhus was born (Voskoglou, 2023). "Smart Aarhus is a link between the public and private sectors, as well as citizens and knowledge institutions when it comes to digital solutions that make Aarhus greener, better, and overall smarter."

Partnerships between the city, the public, the non-governmental and private sectors, as well as universities and citizens, are a way for Smart Aarhus to combine its efforts to find common, effective, and sustainable solutions to the challenges facing modern cities (Baraniewicz-Kotasińska, 2022).

Similar ideas guided the project to build a social air quality measurement network, which has been implemented since 2017 in Gdansk and Gdynia. In a partnership between representatives of business (LPP S.A., the largest employer in the region), a university (WSB Merito University), a non-profit organization such as the Association Forum for the Development of the Gdansk Agglomeration, and with the initial local support of the Gdynia initiative City Common, the project "Tri-City breathes" was launched. The goal was to provide residents with full and reliable knowledge of the actual state of air quality in their residence and to align municipal and provincial policies for improving air quality with the actual state of air quality.

However, similar goals do not mean that the partnership in question can be managed and developed based on the Scandinavian experience. Three decades after the political change in the broader development of Polish cities, we see the manifestations and consequences of revitalization, recomposition, and gentrification (Jaroszevska-Brudnicka, 2012) affecting their future and determining the directions of development. Not always positive, not always in the spirit of Scandinavian traditions of partnership relations between stakeholders. The practical implementation of the goals of smart, sustainable cities by cross-sector partnerships can follow different patterns:

- Scandinavian model - described above using the example of Aarhus, based on co-management and co-management between city stakeholders and citizens. Its basis comes directly from Scandinavian traditions of cooperation.
- The American model - public-private partnerships, a more "commercial" model in which local governments seek to develop new solutions to urban problems based on advanced technologies and entrust public tasks to technology and information technology corporations.

Asian model - where centrally planned initiatives often take the form of peculiar experiments designed to serve economic growth and build technology hubs (Baraniewicz-Kotasińska, 2022).

Local cross-sector partnerships are often based on case studies and practitioner experience. Standardization, by its very nature, is a process of reducing diversity - writing down a standard is always an act of choice: we indicate a recommended course of action that we regard as more desirable (Handzlik et al., 2012). This is a preferable solution in public administration or technical processes (such as obtaining data from measurement networks), but difficult in the creative activities of NGOs or more social processes, building mutual trust between partners.

In this case, we focus, according to Table 1, on stage two of the assumptions for the construction of the testbed (stage one has been completed). The case study of the FRAG / WSB / LPP cross-sector partnership is a research component to understand the processes, benefits and challenges of this type of partnership. In Poland, unlike Denmark, there is not such a rich culture of cooperation between local governments and residents. There is also, of course, no central planning, and the American model, while often welcomed by local governments, is less acceptable to residents and NGOs (which are most often ideologically closest to the Scandinavian model).

The partnership established by the Forum for the Development of Gdansk Agglomeration (as the leader of the project) was to some extent aimed at forcing action on the local government to improve air quality in the city and was not based on partnership relations with the authorities and a willingness to cooperate on the decision-making side.

The basis for the analysis is to identify the goals and motivations of each party involved in the partnership. A company may be interested in improving its public image by engaging in an air quality improvement initiative. A non-governmental organization may seek to improve the living environment of residents and increase public awareness of air pollution problems. A scientific research unit, on the other hand, may have as its main goal to conduct scientific research to understand the scale of the problem and develop effective solutions.

The next step in the analysis is to identify the benefits of partnerships, such as mutual exchange of knowledge and experience, increased access to technological and financial resources, and increased public trust through transparency of activities. Challenges and risks should also be considered, such as cultural and organizational differences between sectors, difficulties in coordinating activities, and conflicts of interest. The case study should also focus on specific partnership activities, such as installing air quality sensors, developing a monitoring and data analysis system, and community education and outreach activities. Ultimately, it should serve as a basis for inferring the effectiveness of cross-sector partnerships and identifying potential areas for improvement and further research.

At this stage of the article's preparation, it is difficult to determine the next stages (third, fourth, and fifth) of the research, assuming that they will be derived from the development of stage two, whose processes have been described above.

Today, all over the world, urbanization processes are taking place under the influence of globalization and technological and technical progress. Globalization is a selective process, that is, it takes place with different intensities at different points in space. Cities that have adequate knowledge and capital resources (including human, economic, and social) are places where innovations are generated (Tarification of benefits or the price of medical services, 2022). These, in turn, become the basis for building a city's competitive advantage and its dynamic growth. Their development then fits into the concept of sustainable development, and can also be referred to as smart development (Stawasz, 2016).

Capturing data simultaneously is not a task assigned only to local governments, businesses, or any other institutions and organizations. It is only possible with the close cooperation of all stakeholders. This is because it is the users of the city who generate the data, or even if the measurements relate to external factors (e.g., environmental factors) this is done on land under their jurisdiction (e.g., an air quality sensor must be located on a city plot or requires cooperation with a private manager). It is representatives of business, the third sector, or academia who collectively can interpret the data in the best possible way. Best understood as the fullest and most multifaceted use of them in city-making processes.

Cross-sector partnerships increase the creativity of decisions and innovation in cities. Each party provides knowledge specific to its sector and brings individual context to the analysis of problems. This makes it easier to reconcile the interests and expectations of different stakeholders and, as a result, develop decisions that are acceptable to all partners (Baraniewicz-Kotasińska, 2022).

2.3. Concept of a model for diagnosing and predicting the condition of Emergency Department patients based on analysis of air quality data

The proposed concept of diagnosing and predicting the condition of patients fits into the issue of urban development, as the design of knowledge bases involves the integration of comprehensive data sources related to demographic factors and knowledge of city residents, as much as urban planning principles and predictive algorithms to support decision-making processes for business processes (Gładysz et al., 2010).

It was assumed that the use of specific algorithms to predict phenomena using indirect data (not directly related to the phenomenon), is not as important an issue as minimizing the prediction error. It was considered that a prediction that has a sufficiently high measure (or low acceptable error) will bring decision-making benefits. The assumptions for building knowledge bases are based on medical considerations, i.e., the impact of urban air quality on the health of residents, and formal business considerations, i.e., the state's responsibility for medical care (Lee et al., 2022, Stat.gov.pl, 2022).

Assumptions for knowledge bases in the business area will enable hospitals to adjust staffing levels in the emergency department accordingly or allow them to optimize resource allocation in the case of multi-department hospitals (Handzlik et al., 2012; Jiang et al., 2023). Simply predicting a patient's condition can help manage the level of medical supplies, ensuring the availability of necessary equipment and drugs. Early detection of potential health problems related to air quality can prompt proactive measures, improving patient outcomes and reducing illness (Jiang et al., 2023; Lalit et al., 2021). It has been hypothesized that earlier knowledge of expected medical conditions can help in the effective selection of patients, providing priority to those most likely to be affected by environmental factors.

In the area of predicted patient length of stay in the emergency department, as well as the number of patients and their condition, it will affect the management of overcrowding in emergency departments, potentially reducing waiting times and improving their overall performance (Peng et al., 2020). Current statistics of both length of stay in hospitals and codes for reasons for hospitalization (National General Hospital Morbidity Survey, 2024, Palus et al., 2023) can provide an empirical interpretation to check the length of stay of patients in hospitals using predictive models. By identifying patterns between air quality and specific health problems, hospitals can take preventive measures, potentially reducing costly long-term treatment, and, according to the authors of the project, can also influence the management of the number of hospital beds and ultimately reduce the social costs of operating a health care system.

Findings from the model may help public health interventions targeting improvements in air quality, thereby reducing ED visits related to environmental factors (Michalak, 2022). The model was built based on experience from the following articles (Gafni-Pappas et al., 2023; Ravindra et al., 2023; Sudarshan et al., 2021). Evidence of the impact of air on patient conditions, supported by data, will help support policy recommendations to improve environmental standards for the benefit of public health on a larger scale.

In healthcare, especially in diagnosing and predicting patients in the ED, we can develop a model that integrates air quality data, patient medical records, environmental factors, and predictive analytics techniques to generate knowledge to support healthcare professionals' decisions.

As stages I, II, and III have been completed stage four is planned:

- Collection and processing of air quality data from available sources (Measurement Data Bank, 2024). Anonymized data of all patients from the emergency department of UCK Gdansk, including diagnoses, vital signs, and demographics (2022 data covering 40,000 patients of the NRA). The next stage will extract relevant features from air quality data (PM2.5 and PM10 dust levels, nitrogen oxides, and sulfur dioxide concentrations). It is then planned to link patient records with relevant air quality data based on temporal correlation from NRA records and spatial distance through a map of patient addresses and air quality meters (Measurement Data Bank, 2024). By reviewing the time series relationships between air quality metrics and patient visits to the emergency department, it plans to extract data features that will be used for model development, particularly NEWS 2 metrics (National Early Warning Score (NEWS), 2017).
- In stage four of the research, supervised learning algorithms will be used to create predictive models, as well as association algorithms and fuzzy logic rules. Prediction of the category of the patient's condition (triage) based on air quality characteristics makes it possible (along with the combination of time norms for the speed of initiation of patient care) to predict the queue status of patients waiting in the ward by predicting the frequency of patient admissions. Prediction of the queue status trend using time series models (ARIMA, LSTM, etc.) in air quality data ultimately allows multiple models to be combined for a more reliable

prediction. Model evaluation and validation is a mechanism for adjusting the hyperparameters of the model and analyzing its sensitivity to so-called "data-drift" effects (Sahiner et al., 2023).

- At this study stage, recall and precision metrics were used as the basis for evaluating classification. To predict the time of each stage of the care process in the UCK emergency department, the errors of MAE and RMSE time estimates were adopted (Sudarshan et al., 2021). Each of these metrics was evaluated by physicians, along with an assessment of their usefulness for planning the use of resources (the work of physicians, the necessary staff, and the impact on the calculation of medical services and their pricing for the National Health Service). Refinement of the model based on the opinions of healthcare professionals and additional data is the subject of further work after piloting the system. The system has also added a metric for classifying the risk of air quality-related diseases.
- An important element of prediction at this research stage is the determination of queue time, which generates the cost aspect. The procedure for valuing medical services for the National Health Service by calculating direct and indirect costs includes the time of the procedure and the time of staff disposition to perform it (Sweeney et al., 2023). Therefore, it can be assumed that "patients in the queue" can generate financial and non-financial costs of the hospital (Bogusiak et al., 2020).
- The summary of this stage will be the implementation and monitoring of a system to support decision-making about the surgical risk of admitting patients is to be a response to the problems of the functioning of the NICU of UCK Gdansk and the ED of Polish hospitals. The proposed solution is already being implemented in 2 stages. Stage one involves the preparation of a pilot of the system's operation, which uses actual data from hospital wards. This data is processed using the technology to build the pilot, which is IBM Node-Red. In the construction of the pilot version, 4 key processes of the operation of hospital emergency departments were taken into account: admitting a patient, performing a triage, performing an epicenter, and discharging a patient from the hospital. Patients' stay times in the NRO were analyzed using queuing processes in message brokers, and then the status of patient queues was visualized, identifying warning states (Figure 1.).



Fig. 1. Prototype of a decision support system for operational risk of admitting patients to the UCK Clinical Emergency Center

- As part of this stage, the developed system will be fed with real data from hospital emergency departments, and the prototype developed in stage one will undergo a containerization process. As part of this stage, a predictive version of the system's operation is also planned to be built based on air data and using ensemble models (Senthil et al., 2021). The purpose of these forecasts is to analyze the potential behavior of hospital emergency departments in 12-hour cycles, to predict the demand for emergency physicians, and the number of patients classified using triage categories. The construction of the forecasting system is planned to be carried out using fuzzy modeling processes, and to apply association rules and the operation of neural networks in data processing. The developed prototype of the system has been installed in the IT infrastructure of the WSB CAS IoT laboratory. It is planned that the target version of the system will be installed in the IBM Cloud as a SaaS service (Fletcher, 2019). Appropriate approval was obtained from the Bioethics Committee to ensure the privacy of patient data.

2.4. The concept of a management model for the development of digital health data, supported by generative artificial intelligence mechanisms

Implementing AI-supported medical systems is a complex field, and experience in this area is currently limited. Holistic implementations of digital medicine centers do not guarantee adequate information sharing and bring risk (Peng et al., 2020). The impact of digital medicine on cities of the future is enormous. The development of AI technology, combined with demographic changes, is causing an increase in medical IT projects. These projects have elaborate system architectures, enormous data-related challenges, and the ethics of using AI (Jiang et al., 2021, Stoumpou et al., 2023).

Real-time processing of large and diverse data (tabular, unstructured, image, and omics) necessitates the use of AI tools, i.e., artificial intelligence algorithms and models, including from systems dedicated exclusively to medical applications (Kannampallil et al., 2011, Smart Aarhus, 2024). The data infrastructure and medical platforms must be ready for the exponential growth in volumes and partners participating in the medical information exchange system (Pablo et al., 2024, Dashkevych et al., 2024). In addition, digital medicine is controlled by industry standards and laws, including regulations on personal and sensitive data and cyber security, which affects implementation complexity (Giacalone et al., 2018;).

Therefore, it seems reasonable to conduct research and develop a methodology for managing the implementation and integration of AI-supported medical systems, i.e., Medical Generative Artificial Intelligence (MG-AI) systems, in the context of the quality of input and learning data, model data, and responses obtained from generative AI. Such a methodology should cover issues specific to the management of medical imaging and binary and omics data, including the identification of tools for assessing the quality of the implementation of an AI-supported medical system, prepare a standard for evaluating prompt quality attributes and methods for assessing the maturity of the solution (Dashkevych et al., 2024, Susha et al., 2023). The model was built based on experience from the following articles (Moulaei et al., 2024; Nova, 2023; Ravindra et al., 2023).

This part of the work will describe the modeling processes for the development of a complex MG-AI medical system using the example of the Interdisciplinary Pomeranian Center for Digital Medicine. The work will present methods for safe, organized, and effective implementation of AI solutions into the health care system.

Preparing a methodology for managing the implementation and integration of medical systems requires a suitable research environment for evaluating the quality of the method and its effects. The research environment will support the iterative work on the MG-AI implementation methodology. Testing and evaluation of the project's core indicators will be conducted in the environment of the Interdisciplinary Pomeranian Digital Medicine Center (IP_CMC) (Medical Research Agency, 2023) . As part of the ongoing project to build a digital medicine solution, several iterative activities will be performed aimed at building a medical information hub for the region, including the preparation of the foundations for open regional exchange of medical data and the implementation of new AI models to enable clinical research.

Among other things, the research work will use the CBR method (An Artificial Intelligence Based Automated Case-Based Reasoning (CBR), 2024, Ociepka, 2011, Raja et al., 2023). In this case, the CBR method will be used to solve problems in the AI project by looking for analogies (similarities) between existing (previous) AI use cases and the results generated by the AI on the IP_CMC platform. The research work is divided into the following stages:

Stage 1 Concept development

In this phase, architectures will be prepared at the technology, application, and data levels for AI models, allowing for targeted clinical trials on, for example:

- simulations, such as the operation of the immune system (Pablo et al., 2024),
- models of patient behavior and reactions to medical procedures,
- Development of new drugs and medical procedures,
- Diagnostic imaging and medical image corrections,
- search for clinical models,
- Personalizing medical procedures,
- precision surgery support.

The premise of the research concept is that generative artificial intelligence can help diagnose and then treat diseases more efficiently and better. Appropriate evaluation indicators for AI models will be prepared to confirm that the AI models being built align with the assumptions.

Stage 2 Assumptions for the construction of the test site

The approach to building an IT solution based on Enterprise Architecture is now being abandoned. Therefore, searching for an optimal solution for the AI model will be based on finding a similar case (retrieval) from a group of cases collected in the case knowledge base. This will create a new case (use case), which will be saved as a new or modified case (*retainment*) in the CBR case knowledge base.

The construction of an AI-supported medical system will be based on the following principles:

- Regional Interoperability.
- Data Sharing.
- Ensure data anonymization and security.
- A coherent view of medical processes.
- Implementation in a way that allows you to gather experience in designing medical systems.
- Iterative and agile approach to development and functionality.

Iteratively conducting the work will provide ample opportunity to experimentally conduct design work and analyze the feasibility of designing arbitrary siloed medical functionality in MG-AI class systems.

Stage 3 Construction of the test bed

At this stage, an appropriate statistical database will be prepared to enable the iterative development of AI models. The design processes will be divided into 3 stages:

- Mapping of processes, results and roles,
- data bin aggregation,
- Preparation of teaching models.

At this stage, MG-AI management process guidelines will also be defined, i.e., handling guidelines for source data, integration, learning, data governance, and security. The inventory of project processes and their classification from the point of view of enterprise architecture layers will also be an effective tool for the subsequent preparation of AI performance indicators. The main idea is to identify several increments, within which the following steps will be carried out:

- Gathering requirements
- Data increments for teaching and research
- Defining the research scope
- Metering
- Collection of results and conclusions
- Modification of requirements

An element to be considered in the work will be the possibility of using the MG-AI use case base from other regional centers and accessing the knowledge base and AI models. This is one element that enables the transfer of MG-AI system design methods to other cities and regions. To do this, it will be necessary to define and develop a consistent framework for processing medical data that can be adapted to any architecture and design framework.

Stage 4 Research Experiments

The MG-SI design process is an intellectual, creative process of a complex nature due to environmental conditions, technology, and organizational culture, and it depends on the talent and ability of the design team. All of these 4 areas, as well as the effectiveness of the IS itself, will be subject to indicator evaluation of the results of the design method. Using evaluation and self-improvement within the CBR method will contribute to the rapid delivery of increments (iterations) of the concepts and solutions created.

The subject of the experiments will also be to determine what effective IT and organizational methods should be used to implement MG-AI. The research team will search for component function structures that meet the design objectives, thus creating valuable solution variants that will feed into the knowledge base as secondary component functions and a history of concept formation. Medical data collected in this way - by the way, as it were - will be able to be collected secondarily as material for teaching AI.

Step 5 Description of experiments for knowledge models

The MG-AI work will use medical data including:

- personal and sensitive data,
- diagnostic tests,

- imaging studies,
- omics research,
- history from the monitoring apparatuses,
- medical records from medical process management systems,
- results of clinical models,
- statistical data required for decision-making,
- reportable and mandatory data,
- medical event history and system logs.

The ongoing study will focus on key factors that must be considered to create sustainable and scalable MG-AI designs. Artificial intelligence (AI) models based on medical data will form the basis for preparing design framework concepts for implementation. The importance of AI in clinical evaluation will grow, and AI tools will become helpful to doctors and researchers. Hence, the reliability of AI performance is important (ArXiv.Org Snapshot, 2024;). Monitoring the growth of indicators describing the quality of AI implementation in projects is essential for properly evaluating AI quality (Abadie et al., 2023, Krup et al., 2018). There are moral dilemmas regarding the use of AI and sensitive data in medicine, so it is important to develop an effective and stable method of AI implementation in the medical field. There is a need to study further the approach to MG-AI system implementation projects, which could increase the efficiency of projects in the medical sector.

2.5. Concept of component commercialization model of students' thesis

The process under which the "Thesis Component Commercialization Model" will be developed is referred to in this study as a subsidiary process. The nature of the component commercialization issues allows for any choice of domain, i.e., business sector, domain, scope, and subject matter of the projects carried out under each process. The auxiliary process, together with the main process, coordinates the development of models that are input to the main model. Figure 3 shows the relationships between the processes focusing on the three management shells: the database and model building area, the central processes and the auxiliary process.

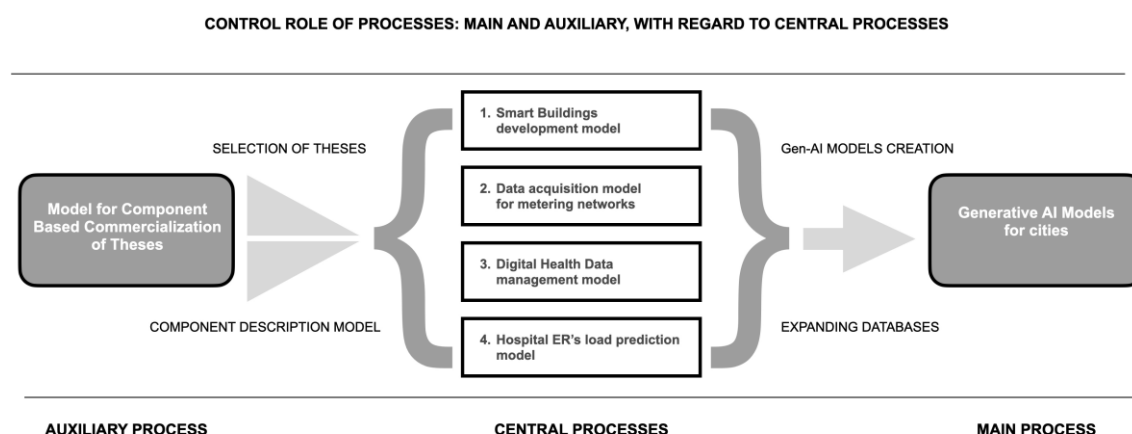


Fig. 2. Coordinating the role of auxiliary and main processes. Own elaboration.

The main objective of the auxiliary process "Model for Component Commercialization of Theses" is to create and test methods for preparing descriptions of theses that would enable their elements to be used in machine learning or the preparation of text fragments that can serve as instructions or commands for generative artificial intelligence systems, so-called prompts. The role of the auxiliary process is to short-circuit the other elements of the project and identify one way to improve urban development.

We assume that the component commercialization of theses will be the basic knowledge resource used in constructing the four main models supporting the processes of future development. These theses will be created in the framework of cooperation between the scientific and research unit and doctoral students who, knowing the development processes of future cities and representing businesses and NGOs, will participate in the implementation of such works.

- The concept of Component Based Commercialization developed at Merito WSB University in Gdansk (Nogalski, 2024) will be applied, which consists in identifying elements of the thesis and treating them as components of larger systems, so that these components gain business potential. The model was built based on experience from the following articles (Dahl et al., 2023, Kosieradzka et al., 2021, Xu et al., 2023). At the core of this concept is the observation, confirmed by the study's authors, that a large percentage of theses have a viable implementation character, and that most of them contain a business component whose potential can only be assessed in the context of a broader group of such elements. The survey also showed that students in most cases agree to commercialize elements of their theses that, without the component method, would not be able to exceed the critical mass enabling standard commercialization paths, such as the creation of a spin-off company.
- Stage one will include the development of a research concept to prepare and test, through a series of experiments, a model for managing the knowledge produced within the project, namely database models, machine learning and artificial intelligence models, and methods for describing and parameterizing the results of the work for use in the component commercialization process.
- In the second stage, a method will be developed for the selection of theses and ways to describe them for generative artificial intelligence. Each central process will be implemented based on a series of theses, the results of which will be described in the form of components prepared for commercialization. As part of this stage, a method of thesis selection will be proposed. Projects on the support of urban management systems are only a small part of the area of cooperation between universities and the socio-economic environment, without loss of generality, a special case of the issues studied within the framework of this project can be used to evaluate the components of the process and build a model.
- The test bed (third stage) will be established in cooperation with external research units, the selection of which will take place in step three. In the first step, general research cooperation will be established with the selected units. Subsequently, the leaders of each central process will establish substantive research cooperation with external research groups. This will allow them to expand the scope of the research and take into account additional aspects of the issues under study that will become apparent after the change of research perspective.
- Stage four is the development of a system for which the thesis elements, once properly parameterized and described, will be the input for the main process responsible for creating generative artificial intelligence models. A key element of this stage will be the selection of test scenarios that allow for the gradual development of the system, which can be done by strictly controlling the input data. Learning the system, parameterizing the models, and "promatizing" the generative artificial intelligence is such a complex task that the project should adopt such ways of preparing the input data that it does not require repeating the entire process of learning the system multiple times.
- In the fifth stage, databases will be created to feed the main process of the project. Each central model will be based on the cooperation of the leader - a doctoral student - with a group of students who, using the methods of description and parameterization of the thesis results developed in the earlier stages, will allow the model to be verified from the point of view of Component-Based Commercialization methods. The developed model for describing the components of the thesis will be tested in dozens of independent experiments and verified using Case Based Reasoning.

By using the auxiliary process to coordinate the other processes, a model for the use of thesis elements in component commercialization can be developed and tested in parallel with the construction of knowledge bases for generative artificial intelligence. As a result, this will help expand the university's business environment, strengthen triple-helix cooperation, and contribute to the retention of students in the region, i.e. increase their retention. In the long term, research can be planned to find a positive correlation between the retention of graduates and their active participation in component commercialization processes.

The question still remains: what is the purpose of introducing an auxiliary process? Is it not possible to conduct research only within the framework of the main process and the central processes? The main goal of the planned project is to develop urban development processes. This can only be done in cooperation with the socio-business environment of the research unit. According to the triple-helix model, introduced by Etzkowitz and Leydesdorff (Medical Research Agency, 2023), close cooperation between universities, industry, and local authorities contributes to the development of innovative concepts, encouraging academia to go beyond its standard areas of activity, namely teaching and research.

2.6. Concept of generative artificial intelligence models for cities of the future

Artificial intelligence generative system models for cities are a research area where artificial intelligence technologies are used to analyze, design, and optimize urban systems. These models aim to improve city

operations, increase efficiency, and minimize negative environmental impacts. Increasingly, this type of support can be used to design and modernize urban infrastructure (Kucirkova et al., 2023).

The use of technologies from the field of AI for the design and maintenance of urban infrastructure may be gaining importance, as the information systems implemented in Cities are generating an increasing amount of data. This data, can be successfully used to optimize many processes. Here are some key aspects for generative artificial intelligence system models for cities that can benefit from such solutions:

1. **Traffic and Transportation Analysis:** Generative models can be used to analyze traffic and public transportation in cities. They predict traffic flow, identify traffic jams, suggest optimal routes and support the design of intelligent transportation systems.
2. **Optimizing Urban Space:** Generative systems can help design and optimize urban space. They support urban planning, taking into account aspects such as building location, public spaces, green spaces and infrastructure.
3. **Energy Efficiency:** Generative models can support the design of energy-efficient cities. They help optimize power grids, forecast energy consumption, and identify areas where energy efficiency solutions can be applied.
4. **Waste Management:** Artificial intelligence can be used to optimize urban waste management. Generative models can forecast waste generation, optimize trash collection routes, and support recycling and disposal.
5. **Smart Energy Systems:** The introduction of Smart Grids can be supported by generative models that forecast energy demand, identify areas of excess consumption, and support the integration of renewable energy sources.
6. **Accessibility For Citizens:** Generative models can support accessibility to public services such as street lighting, bus stops, and access to parks. By analyzing pedestrian traffic and demographics, a citizen-friendly urban environment can be designed.
7. **Accident and Hazard Simulations:** Using generative models to simulate various scenarios of traffic accidents, natural disasters or other hazards, helping cities better prepare for emergencies.
8. **Personalized Urban Development Proposals:** Based on analysis of residents' preferences and demographics, generative models can propose personalized development solutions for an urban area.

The introduction of artificial intelligence into urban planning and management has the potential to significantly improve the quality of life for residents, sustainability and efficiency of various urban systems. However, at the same time, it is important to take into account aspects related to privacy, ethics and responsible use of these technologies. In order for this to be used effectively, however, new solutions are needed that make full use not only of Smart Cities' urban infrastructure but, above all, of historical data (Fig.4). The model was built based on experience from the following articles (Chang et al., 2023, Dashkevych et al., 2024, Wu et al., 2022)



Fig. 3. of the concept of using some key aspects for Artificial Intelligence Generative Systems Models for Cities. The figure was generated by ChatGPT according to expected assumptions.

Stage I consists in conducting research and selecting the optimal Language Model in terms of implementing such a solution on the infrastructure of the WSB Laboratory. It should be mentioned that currently technologies of this type are developing very rapidly and there are many proposals on the market. The selection of an appropriate language model for generative artificial intelligence systems for cities must take into account the specifics of the project and integrate all the elements in it. Choosing the right language model may also force a change in the existing infrastructure of the WSB Laboratory. Some solutions (language models), have a wide more hardware requirements. The solution selection stage seems crucial to integrate all parts and elements.

Stage 2 Assumptions for the construction of the test site. The infrastructure of the WSB IoT Laboratory will be used to build the testbed. The first stage will consist of selecting a solution - a language model. Stage I will have a huge impact on the WSB Laboratory's hardware environment. This means that only then will it be possible to make some changes to the environment itself. These elements will be dedicated in Stage II, where, based on the generated recommendations, the process of building the testbed will begin. Stage 2 should generate Conclusions and recommendations on what solution the Presented Project (Urban Development guided by knowledge base design processes of generative artificial intelligence systems) will use. This stage will be the input material for the next Stage 3. This may mean that the construction of the research environment will be implemented on the basis of the WSB IoT Laboratory Infrastructure. It may also happen that the selected language model will require investment in the computing power of the WSB Laboratory infrastructure itself.

Stage 3 Construction of the test bed. Conclusions from Phase 2 will be to investigate the optimal use of the various language models available on the market. Develop recommendations and generate recommendations for possible expansion of the WSB Laboratory Infrastructure. These recommendations will provide the necessary material for the construction of the target test bed.

Stage 4 Research experiment. This Stage will consist of generating a recommendation as to the target solution, which is to prepare a strategy for using a specific solution under the recommendation system for Urban development-guided design processes through generative artificial intelligence systems. The proposed experiment in this Phase should answer the question of which solution to use to build a recommendation system. In the accumulated literature, mostly two potential scenarios are used.

The first scenario is to use the solution of a generally available language model. On the basis of such a Model, an own language model will be proposed, dedicated to the needs of the project. This stage will consist of organizing a team of students to adequately "teach" the selected model to ensure the uniqueness and specificity of the resulting recommendation system. Using a set of labels, and based on historical data, in-house "training" of the model will be carried out with the student team. This approach is very expensive and time-consuming. However, it gives great results.

The second scenario involves the use of Retrieval Augmented Generation (RAG) is a method that enriches prompts, and the model queries used in Generative AI, by attaching context containing relevant information from external data sources. This technique enhances the ability of Large Language Models (LLMs) to work with custom data. This scenario seems more attractive. The RAG method of prompt enrichment does not require training a custom model. The effects can be seen in a short time.

Both scenarios have their strengths and weaknesses, which will be reviewed in the proposed and selected scenario. However, two scenarios cannot be implemented simultaneously in the Stage. Therefore, the selection of the appropriate scenario will be implemented in Stage 3 and in Stage 4.

Stage 5 Description of experiments for knowledge models. On the basis of the experiments conducted, a description and recommendations will be made. The description of experiments for knowledge models for smart cities can cover a variety of aspects, depending on the specific research or application task. The following is a general outline of the description of experiments, which can be adapted to specific research needs:

1. Purpose of the Experiment: To begin, it is important to define the purpose of the experiment. Is the study intended to evaluate the effectiveness of a particular model in solving a specific problem in smart cities, or is it intended to compare different models in terms of their performance or other metrics?
2. Selection of Models: You need to select the specific knowledge models to be experimented on. These can be models based on artificial intelligence, machine learning, or even traditional models. It is important that these models are relevant to the problem under study and meet the specified selection criteria.
3. Task Selection: Next, define the specific problem or task that will be the subject of the experiment. This could be traffic forecasting, energy optimization, waste management, or other smart city applications.
4. Data Preparation: The next step is to prepare the data for the experiment. Depending on the task, this could be data on traffic, energy consumption, city demographics, or other data related to city operations.
5. Experiment Design: The experiment should be carefully designed, defining evaluation measures, methods, and how to divide the data into training, validation, and test sets. It is also important to define the model parameters and possible hyperparameters.
6. Implementation and Training of Models: The next step is implementing and training the selected models on the prepared data. Taking care of proper cross-validation techniques and hyperparameter tuning for optimal results is worthwhile.
7. Evaluation of Results: After training the models, evaluate the results. This may include analysis of quality indicators, such as accuracy, precision, and sensitivity, depending on the type of task.
8. Conclusions: Based on the experiment results, it is possible to conclude the effectiveness of the tested models in solving the problem and identify potential weaknesses and possible directions for further research and development.

9. Publication of Results: Eventually, the results of the experiment can be published in the form of a scientific article, technical report, or conference presentation to share the knowledge gained with other researchers and practitioners in the field of smart cities.

2.7 Modeling LLM RAG systems governance in the development of future cities

The management of artificial intelligence (AI) technologies is a significant area of research and practice due to their growing applications in various fields. In particular, large language models (LLMs) and the Retrieval-Augmented Generation (RAG) technique, which integrates the capabilities of LLMs with the process of retrieving and utilizing external data, generate new challenges related to AI operations management. These issues encompass both technical and ethical aspects, including efficiency, transparency, and the responsible use of these technologies.

RAG (Retrieval-Augmented Generation) systems can support the management of complex urban ecosystems by utilizing data from various sources, such as IoT sensors, monitoring systems, resident reports, and public databases. However, the lack of appropriate governance mechanisms in such systems can lead to issues related to transparency, ethics, biases, and data security. The development of a governance model for RAG systems in the smart cities of the future aims to establish effective mechanisms that enable:

- Managing large datasets in real-time,
- Delivering precise information to the LLM model in accordance with the ongoing context,
- Verifying and auditing content generated by language models,
- Considering the legal and ethical aspects of data usage.

Stage 1: Concept Development

The first stage of the study will focus on analyzing and developing the theoretical foundations of RAG Governance mechanisms based on patient data, with consideration of their potential application in smart city systems of the future. The goal of this stage will be to identify key challenges and opportunities related to the use of RAG systems for managing sensitive data. Particular attention will be given to management, verification, and audit mechanisms for patient data that could be adapted to other areas of smart city operations, such as transportation management, public safety, or critical infrastructure. The concept development will examine aspects such as:

- Management of sensitive data: An analysis of methods for anonymizing and pseudonymizing patient data to ensure its security within RAG systems.
- Audit and verification mechanisms: Processes will be designed to check the correctness and compliance of content generated by LLM models based on patient data and assess their scalability within urban information systems.

This stage will create a vision for the RAG Governance system as a universal tool that could be applied in various contexts, with a particular focus on transferring insights and mechanisms developed from patient data to the broader context of smart cities.

Stage 2: Research Station Design Assumptions

At this stage, a research environment will be designed at the WSB Merito Gdańsk computer lab. First, an analysis of the laboratory infrastructure will be conducted, including an evaluation of available computer systems, data management software, and LLM models. Based on this, the technical and functional assumptions for the research system will be defined. Patient data will be anonymized using appropriate tools (e.g., pseudonymization and differential privacy) and will include information on diagnoses, therapies, medical histories, and demographic characteristics. Mechanisms enabling the integration of the database with the RAG model and governance modules will be designed, including:

- Data flow monitoring
- Automatic audit and verification of system-generated content
- Adaptive mechanisms for adjusting system actions to changing needs

Test scenarios will also be developed for laboratory execution, such as therapeutic recommendations based on similar cases or data verification in crisis situations (e.g., pandemics).

Stage 3: Research Station Construction

At this stage, the technical infrastructure for the research system will be implemented. The first step will be the implementation of the patient database. The data will be appropriately anonymized and transformed according to

legal and ethical regulations, then loaded into a database management system that supports fast data retrieval and analysis (e.g., PostgreSQL, MongoDB).

The database will be integrated with the LLM model within the RAG architecture, enabling content and recommendations to be generated based on patient data. Governance modules will be implemented to ensure data management, verification, and auditing:

- Management module: This will control access to data and monitor its flow, ensuring compliance with data protection and information security principles.
- Verification module: Designed to automatically check the validity of input data and ensure that results generated by the model are medically relevant.
- Audit module: This will analyze model-generated content, verifying compliance with legal and ethical regulations and eliminating potential discrepancies.
- Predictive analysis module: This will be used to predict trends based on patient data, such as diagnostic patterns or therapy effectiveness, supporting real-time decision-making. Once the research station is constructed, technical tests will be conducted to assess the integration accuracy and alignment with design assumptions.

Stage 4: Research Experiments

Experiments will be conducted in a laboratory environment where the research system will be tested in various medical scenarios. Simulations will include situations such as rare disease case analyses, therapeutic recommendations, and crisis situations, such as an emergency intake of a large number of patients. The system's effectiveness will be assessed in terms of the accuracy of generated recommendations, real-time data management efficiency, and compliance with legal and ethical regulations. System performance data, such as response times, result accuracy, and user feedback (e.g., medical experts), will be collected and analyzed.

Stage 5: Experiment Descriptions for Knowledge Models

The final stage of the research will focus on documenting the experiments and developing knowledge models that incorporate management, verification, auditing mechanisms, and adaptive system actions in the context of governance challenges based on patient data. Based on the experiment results, knowledge models and practical recommendations will be created, indicating how to implement research outcomes in health management systems and other areas of smart cities, such as transportation or public safety management.

The analysis will include evaluating the accuracy of recommendations (frequency of correct and useful suggestions), data processing times (system's ability to operate in real-time), compliance with legal and ethical regulations (percentage of decisions meeting legal requirements), and the quality of content audits (effectiveness in identifying potential errors in generated content). A summary of the results will help assess the effectiveness and potential application of the RAG Governance model in various sectors of smart city operations.

3. Discussion on the usefulness of the developed concepts and modeling processes for cities of the future

The article presents a vision of the functioning of future cities based on four models proposed for implementation: research laboratories analyzing the operation of intelligent buildings, creating inter-sectoral partnerships using data from intelligent networks, using common medical data for the operation of hospitals and the work of emergency departments analyzing patient data on the example of data from air quality systems. The presented models are conceptual models in which the authors present proposals for solutions assuming that generative artificial intelligence mechanisms will support the resources used in cities.

The starting point was an analysis of the state of the literature showing that both solutions from before the use of generative artificial intelligence based on machine learning mechanisms are used (Ravindra et al., 2023) as well as those that show the conditions for the use of generative artificial intelligence in the development of cities (Barroso et al., 2023, Khatibi, 2023, Moulaci et al., 2024, Nova, 2023, Reddy, 2024, Rodríguez-Gallego et al., 2023, Sadabadi et al., 2024, Sudarshan et al., 2021, Surit et al., 2023, Tan et al., 2023). It was assumed that the analysis of these publications would allow for embedding the proposed models in the development environment of future cities. While the analysis of the state of the literature refers to general issues concerning the mechanisms of functioning of partnerships (Barroso et al., 2023, Rodríguez-Gallego et al., 2023), the method of obtaining medical data (Moulaci et al., 2024, Reddy, 2024) or the creation of systems for diagnosing patients (Gafni-Pappas et al., 2023, Sudarshan et al., 2021) analyzing existing processes and their threats and the technologies used, the authors in their models, using this information, precisely define how these models are to function in the Gdańsk agglomeration.

Therefore, analyzing the state of the literature was necessary to diagnose the state of research and show the importance of individual processes so that they can be precisely applied in the models created. In the case of

building a model for the development of intelligent buildings (Barroso et al., 2023, Barroso et al., 2023, Rodríguez-Gallego et al., 2023), it was possible to show the importance of data, while the model proposal contains information on the types of data and the method of their transfer between laboratories. The model proposal allows for the importance of data transfer processes for the durability of intelligent buildings. In the case of creating inter-sectoral partnerships, the analysis of the state of the literature (Sadabadi et al., 2024, Surit et al., 2023, Tan et al., 2023) indicated the need to integrate the city processes with the processes of developing inter-sectoral partnerships, which allowed for the assessment of the partnerships existing in the Tri-City agglomeration.

The model's description confirmed that the transfer of data and the functioning of partnerships correspond to what is currently being implemented in the world. Therefore, it was difficult to show the implementation of subsequent stages of the development of these partnerships in this part of the work because their operation depends so much on the development of cities. In the case of the concept of a model for diagnosing and forecasting the condition of clinical patients in emergency departments, the analysis of the literature (Reddy, 2024, Moulai et al., 2024, Nova, 2023) showed the importance of generative artificial intelligence from the point of view of the possibilities of using this technology.

It showed the limitations of their use and the need to analyze environments to assess the usefulness of these technologies. In turn, the presented model has already received such acceptance and provides the possibility of implementing generative artificial intelligence technology. In the case of the concept of a model for managing the development of digital medical data, the literature (Gafni-Pappas et al., 2023, Ravindra et al., 2023, Sudarshan et al., 2021) indicated the existing processing mechanisms and only then suggested the introduction of generative artificial intelligence.

The model concept presented in the article is based on a project in which generative artificial intelligence is already used. Therefore, this analysis of the state and literature presented at the beginning seems necessary because it shows the conditions for developing the models proposed in the work. These conditions, in turn, provide a basis for implementing existing models in the Gdańsk agglomeration based on these conditions. Building models would be difficult without these conditions, especially in the subsequent phases.

The analysis of the literature also shows that in the case of the concept of the model for managing the development of digital data and the development of clinical emergency departments, we are much further ahead of the state of the literature, while in the case of the first two models we are only at the initial stage.

4. Conclusions

1. The article presents the concept of four models supporting the development of cities of the future. These are the models: the development of intelligent buildings based on the functioning of research laboratories, the model for managing the development of inter-sectoral partnerships, the model for diagnosing and forecasting the condition of patients in emergency departments, and the model for developing digital medical data.

2. For these models to be implemented in future cities, it is necessary to use three auxiliary models. The first is related to the support of the work of the intelligent city by scientific and research units and the commercialization of components of the diploma theses of students from these units. The second is the creation of generative artificial intelligence models for these cities based on data obtained from these models. The third is the use of Governance processes as a bridge connecting the results of these models with the development of generative artificial intelligence systems. This additional model is added to this work but is so important for processing data and documents from the four basic models.

3. The analysis of the state of the literature has shown that in the case of the first two models, we are at the initial stage, and we are building the concept of these models with a very difficult definition of the subsequent phases of development. Regarding the two remaining models of development of clinical emergency departments and systems for them and the use of medical data, we are further along because projects are being implemented. In both of these areas, the opportunity for developing these models is undoubtedly the availability of data.

4. In all four models proposed for implementation, the conditions for creating these models seem to be a threat. The literature analysis has shown how these threats can be eliminated, and these models can be implemented.

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