ISSN 2664-9969

UDC 004.8:004.75
DOI: 10.15587/2706-5448.2023.285935

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GENERALIZED INFORMATION WITH EXAMPLES ON THE POSSIBILITY OF USING A SERVICE-ORIENTED APPROACH AND ARTIFICIAL INTELLIGENCE TECHNOLOGIES IN THE INDUSTRY OF E-HEALTH

The object of the research is the review of ways of implementing service-oriented approaches (SOA) and artificial intelligence (AI) technologies in modern healthcare systems. The generalization of these ways will allow to cope with complex modern challenges, such as increasing demand for medical services, growing volumes of data, and the need for high-quality and effective treatment. This work is aimed at this.

The field of e-Health is rapidly gaining popularity and combines many different systems. But due to the large number of tools and system providers with different architectures, there is a problem that different systems are difficult or impossible to integrate and connect with each other.

It is shown that the use of SOA makes it possible to break down complex systems into separate services that can interact with each other to ensure fast and accurate data processing, effective management of medical resources, and improvement of the quality of medical services. AI can be used to analyze large volumes of medical data, predict risks, diagnose diseases, and develop individualized treatment plans. The use of AI in healthcare systems helps improve diagnostic accuracy, reduce treatment times, and improve patient outcomes. The synergy of SOA and AI in health care systems is important when SOA provides the means to integrate various AI solutions, which allows for the interaction of different services and the exchange of data to ensure effective treatment and collaboration between medical professionals and artificial intelligence systems. Such distribution of systems makes it possible to scale them without affecting other services that are already running. Therefore, it becomes possible to use unified data transfer protocols and combine different services into one system without radically changing the codebase and building additional layers of abstraction for interaction between services that cannot be combined in one system. Examples of the use of SOA and AI in modern health care systems to improve the quality of medical services, optimize resources and ensure an individual and effective approach to patient treatment, which can be used at the next stages of medical reform in Ukraine, are considered.

Keywords: *service-oriented approach, weak link, web services, artificial intelligence, machine learning, body sensors, remote monitoring.*

Received date: 10.06.2023
Accepted date: 03.08.2023
Published date: 17.08.2023

How to cite
Petrenko, A., Boloban, O. (2023). Generalized information with examples on the possibility of using a service-oriented approach and artificial intelligence technologies in the industry of e-Health. Technology Audit and Production Reserves, 4 (2 (72)), 10–17. doi: https://doi.org/10.15587/2706-5448.2023.285935

1. Introduction

In the world, the boom in electronic healthcare (e-Health) is growing *as a new style of providing patients with a wide range of medical services for prevention, diagnosis, treatment, and monitoring* [1–3], *the basic components* of which are:

– *Electronic health record (EHR),* which allows to organize the transfer of patient data between different medical professionals (general practitioners, specialists in certain diseases, etc.);

– *Computerization of the doctor's work:* compiling in electronic form patient treatment routes and requests for diagnostic tests with receiving answers-results;

– *ePrescription:* issuing prescriptions to patients with their simultaneous electronic transmission to pharmacists;

– *Clinical decision support system (CDSS)*: provision of information for specialists in electronic form about regulations and standards for diagnosis and treatment of patients;

– *Telemedicine*: physical and psychological diagnosis and treatment of patients at a distance, including telemonitoring of patient states;

– *Consumer health informatics*: use of information resources for patients on medical topics about a healthy lifestyle or treatment of certain diseases;

– *Health knowledge management*: providing doctors with reviews of the latest medical journals, guidelines on best treatment practices or epidemiological observations, including Medscape and MDLinx resources, etc.;

– *Virtual healthcare teams*, consisting of specialists of various profiles, who collaborate and exchange information about patients using digital equipment;
– *Mobile medicine (m-Health),* which includes the use of mobile devices to collect aggregated data about a patient's health, providing this information to practitioners, researchers, and patients themselves, as well as real-time monitoring of the patient's vital organs and direct provision of medical assistance (using mobile telemedicine);
– *Medical research* based on using high-performance distributed infrastructures, the powerful computing resources of which and data management capabilities allow the processing of large volumes of heterogeneous data;
– *Healthcare information systems*, which use software to plan doctors' appointment schedules, manage patient data, manage laboratory schedules, interact with insurance agencies, and perform other administrative tasks related to the organization of healthcare.

It is estimated that thanks to new information technologies, it is possible to reduce the costs of medical care for the elderly by 25 %, and maternal and child mortality by 30 %. In addition, these technologies will make it possible to increase the efficiency of doctors in rural areas: each doctor will be able to serve twice as many patients, which will seriously improve the health indicators of the population in the face of an acute shortage of doctors in the periphery.

The current concept of medical reform in Ukraine is based mainly on the last of the above-listed components of e-Health, namely: on health care information systems [4]. The implementation of the first stage of the medical reform called MVP (minimum viable product) was carried out, which is designed, firstly, to implement the basic necessary functionality to support the primary care reform, and, secondly, to lay the foundations and create the infrastructure for e-Health at the national level. Registers of patients, healthcare facilities, and medical workers are being created. With data in these registers, the system can link the patient, family doctor, and healthcare provider to the appropriate contract in the contract register. Having information from the patient register, the register of medical professionals, and the register of medicines, the system can generate an electronic prescription (e-prescription) for a specific patient with a specific active substance and dosage, as well as generate payments according to the number of patients served.

Russia's aggression slowed further deepening of the reform. In particular, use mobile phones in the field of health monitoring, which provide new means of collecting information both manually and automatically in many fields. Many of today's phones have a variety of built-in sensors, such as a microphone, camera, gyroscope, accelerometer, compass, proximity sensors, GPS, and flashlight. For example, the latest MediaTek Sensio module built into a smartphone provides 6 functions [5]: measure heart rate, heart rate variability, blood pressure, peripheral oxygen saturation (SpO_2) and records electrocardiogram (ECG) and photoplethysmogram (PPG). It uses a combination of LEDs and a light-sensitive sensor to measure the absorption of red and infrared light by the fingertips. To record an ECG and to record an ECG and PPG, the user will need to place the fingers of each hand on the electrodes mounted on the sides of the phone.

New generations of professional medical sensors can easily connect to smartphones and directly transmit sensing results. This created a more efficient and convenient way to collect information about people's health in the form of blood pressure, oxygen saturation, blood glucose, pulse, electrocardiography (ECG), and electroencephalogram (EEG) data. Therefore, at the next stage of medical reform in post-war Ukraine, it will be necessary to solve the following tasks in the field of m-Health:
– *Creation of a mobile platform* that ensures informed decision-making regarding the treatment of patients by doctors through monitoring patients' electronic medical records from their smartphones or tablets.
– *Development of the basic components of the platform*: the Repository of services for patient care (*care services*), for planning and carrying out treatment (*treatment services*), and ensuring the functioning of the entire system (*management services*).
– *Modification of the structure of healthcare* taking into account m-Health tools based on the application of Internet of Things technologies, which involve the connection of many devices to the network and thereby increase its vulnerability from the point of view of security.
– *Implementation of a service-oriented approach* (SOA) to the composition of medical applications for the patient, the doctor, and the functioning of the entire mobile platform. This speeds up the process of their creation and makes it flexible, such that modernization and adaptation to the tasks of supporting specific routes of treatment of individual patients are provided by scaling services: excluding some of them, adding new ones, replacing some with others of the same purpose.
– *Transferring all medical services and applications to the cloud*, which leads to a reduction in capital costs and the use of existing assets, increasing the speed and flexibility of developing and providing new services, and effective management of customer relations in the cloud (for example, billing).
– *Implementation of artificial intelligence (AI) technologies* to improve the efficiency of medical procedures for monitoring and treating patients, for making decisions.

Therefore, the purpose of the work is to summarize information with examples about the possibilities of using a service-oriented approach (SOA) and artificial intelligence (AI) technologies in the field of e-Health.

2. Materials and Methods

Service Oriented Architecture (SOA) is an approach to software design that allows applications to be developed as a set of loosely connected services. These services can be reused and combined in various ways to create new applications, which contributes to modularity, flexibility and versatility [1–3]. In SOA, services are independent functional units that can be accessed using standard protocols such as HTTP or SOAP, and are defined by their input and output data and behaviour. Services are typically designed to be self-contained and manage specific business functionality, such as customer management or order processing.

SOA allows to combine and integrate various services to create new applications and improve existing ones. This allows developers to quickly respond to changes in business requirements with less risk, as they can make changes to individual services without affecting the entire system as a whole. SOA implementation also promotes interoperability and reduces dependency on developers, as services can be developed and implemented by different developers and used by different applications. A successful SOA implementation requires a clear understanding of the business processes and functionality that are implemented through services, and the development of appropriate governance processes to ensure proper management and integration of services. Overall, SOA can help organizations reduce costs, improve agility, and increase innovation, but requires careful planning and implementation to achieve the desired results.

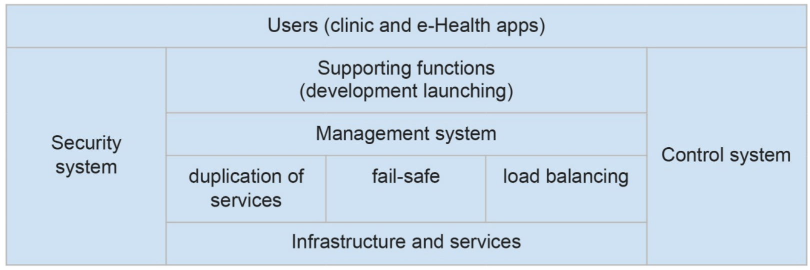

Fig. 1. SOA for the e-Health model [9]

SOA can be effectively used in a smart hospital to create a more integrated, flexible and efficient healthcare system. Below are some of the benefits of using SOA in a smart hospital [6–8]:

– *Integration*: SOA enables the integration and connection of various systems and applications in a smart hospital, facilitating the access and sharing of patient information between healthcare professionals.
– *Reusability*: Services can be reused across different applications, reducing the time and resources needed to develop new applications and making it easier to maintain existing ones.
– *Flexibility*: SOA allows changes to be made to individual services without impacting the rest of the system, allowing the smart hospital to easily adapt to changing business requirements and patient needs.
– *Interoperability with other systems*: Services can be developed and implemented by different providers, facilitating interoperability and reducing dependency on a particular provider. This allows the smart hospital to choose the best solutions for its needs.
– *Data management*: SOA helps improve the management and sharing of patient data, allowing healthcare professionals to quickly and easily access the information they need.

2.1. SOA architecture for the e-Health model. The SOA for e-Health model consists of six main components that are responsible for the interaction between consumers (at the top level) and healthcare services (at the bottom level), as shown in Fig. 1 [9]:

– *Consumers* are hospitals, medical personnel or eHealth software applications.
– *Support functions* help consumers discover, deploy and invoke healthcare and infrastructure services.
– *The management system* ensures high availability, reliability, accuracy and quality of services. This layer uses different algorithms to achieve objectives such as service redundancy, fault tolerance, and load balancing.
– *Infrastructures and services* are a container for the deployment of healthcare services.
– *A security system* guarantees access control and ensures that certain consumers have the right and privileges to use certain resources or a specified level of services.
– *The control system* basically controls the flow of messages from one level to another. Messages in an open standard format are transmitted from consumers to resources through system layers that support data interconnection.

Based on this basic framework, a monitoring system can be developed to transmit sensor data from the patient to hospitals or e-Health software applications.

2.2. Development and implementation of SOA in medical systems. Various technologies and standards are used in the medical field to create service-oriented architecture (SOA). Some of them are listed below:

– *Web Services*: Web services are a key technology for implementing SOA in the medical field. They allow to create services that can be accessed via the Internet. Web services typically use data transfer protocols such as HTTP and SOAP to exchange messages and call services.
– *HL7 (Health Level Seven):* HL7 is a standard for medical information exchange and system integration in the medical field. It uses XML or JSON to represent data and defines standardized messages to exchange data between different healthcare systems and services.
– *FHIR (Fast Healthcare Interoperability Resources):* FHIR is a modern standard for sharing healthcare information in a format that is easy to understand and process for different systems. FHIR uses RESTful principles and uses standard HTTP requests to access medical information and call services.
– *Cloud Computing*: The use of cloud technologies in the medical field allows for the scalability and availability of SOA services. Cloud platforms provide flexibility and broad access to the computing resources needed to deploy and execute medical services.
– *Big Data and analytics*: large amounts of medical data require the use of Big Data and analytics technologies to process, analyze and obtain valuable information. This helps identify trends, improve diagnosis and treatment, and enable personalized medicine.

These technologies, along with other tools and solutions, help build a powerful and effective SOA architecture for healthcare systems, facilitating integration, reuse of components, and facilitating data sharing in this area. Compatibility of medical services for groups of patients with different diseases can be achieved with the help of a medical platform, which consists of:

– *Block of patient services* and portable diagnostic devices.
– *Cloud platform* for storage and processing of medical data (in particular, EHR).
– *Block of services of medical workers* (Fig. 2).

A network of body sensors is used to continuously monitor and record the vital parameters of patients suffering from chronic diseases such as diabetes, asthma, heart attacks, etc. A patient can be warned, for example, about heart attacks even before they occur by measuring changes in its vital signs.

A cloud platform uses networks of remote servers located on the Internet to store, manage, and process data, rather than a local server or personal computer. It also contains a repository of EHR and patient health data that is obtained from various sources.

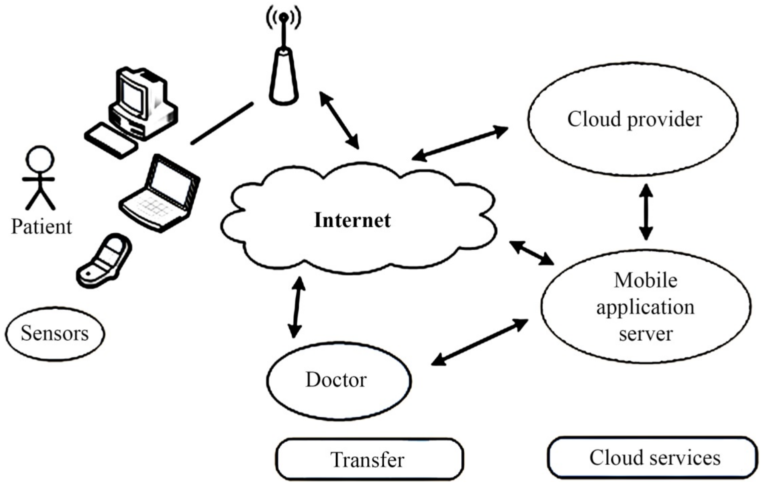

Fig. 2. Organization of medical services in the cloud

2.3. Cloud services. To build SOA in the field of medicine, it is best to use cloud resources such as AWS or Azure, they offer a variety of services that help process data, store personal data in safe places, protect services and data from hacking, and much more. For example, Amazon Web Services (AWS) provides a wide range of services that can be used to build SOA (Service-Oriented Architecture) in medical systems. Here are some key AWS services that it is possible to use [10]:

– *Amazon EC2 (Elastic Compute Cloud)*: EC2 provides scalable computing resources in the cloud. It is possible to use EC2 to deploy and manage virtual servers that will run SOA services.

– *Amazon S3 (Simple Storage Service)*: S3 allows to store large amounts of data in cloud storage. It is possible to use S3 to store medical data, logs, configuration files, and other resources needed to run services in SOA.

– *Amazon RDS (Relational Database Service)*: RDS provides administration of relational databases in the cloud. It is possible to use RDS to store and manage medical information that requires structured storage, such as patient data or medical records.

– *AWS Lambda*: Lambda allows to execute code without having to manage the infrastructure. It is possible to use Lambda to create microservices that are responsible for specific functions in SOA, such as image processing or data analytics.

– *Amazon API Gateway*: API Gateway provides the means to create, publish, and manage APIs. It is possible to use API Gateway to call and manage external and internal services in SOA, providing standardized access to system functionality.

– *Amazon SQS (Simple Queue Service)*: SQS provides a message queuing service that allows asynchronous communication between services. It is possible to use SQS to pass messages between SOA components, providing flexible and reliable data exchange.

AWS provides, in particular, a robust cloud platform for deploying microservices that facilitate the integration of AI into existing SOA frameworks.

3. Results and Discussion

Recent advances in artificial intelligence (AI) have caused significant transformations in healthcare, prompting experts to debate whether AI doctors could eventually replace humans in the future. It is believed that humans will not be replaced by machines in the foreseeable future, but AI can certainly help doctors make better clinical decisions or even replace human intervention in certain functional areas of healthcare (e. g., radiology). The increase in the availability of medical data and the rapid development of analytical methods for processing big data have made it possible to successfully apply AI in health care. With the help of powerful AI technologies, it is possible to examine clinical data in more detail and make a more correct medical diagnosis hidden in a large amount of data, which in turn can help in making clinical decisions [11, 12].

Artificial Intelligence (AI) devices basically fall into two main categories.

The first category includes machine learning (ML) techniques that analyze structured data such as images, genetic data, and ECG data. In medical applications, ML procedures attempt to group patient characteristics or determine the probability of disease development [13, 14]. The second category includes natural language processing (NLP) techniques that extract information from unstructured data such as clinical records/medical journals to supplement and enrich structured medical data. NLP procedures are aimed at transforming texts into machine-readable structured data, which can then be processed and ready for analysis by ML methods [15].

Deep learning (DL) techniques, unlike other methods, are based on the fact that machines independently learn optimal characteristics without any human direction, allowing to automatically discover latent data relationships and recognize partners that may be unknown or hidden. These layers are usually arranged sequentially and are associated with a large number of primitive non-linear operations. First, one layer is represented by the input data, then it sends the output to the next layer, where the data is transformed into a more abstract representation. Data flows through the layers of the system until the input data space is iteratively transformed to a state where the descriptions of the data are distinct (Fig. 3). With this approach, very complex functions can be studied [16].

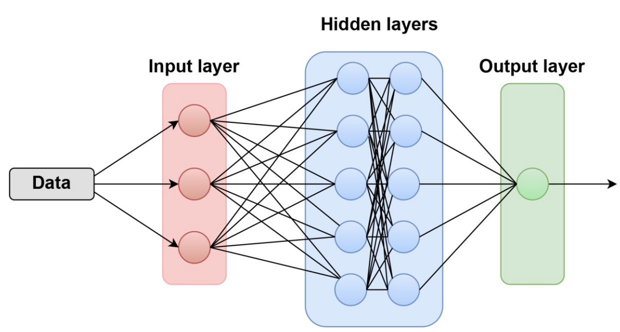

Fig. 3. Deep neural network, simplified

DL performs deeper hierarchical characterization and efficiently identifies remote dependencies in data [17]. This approach has achieved great success in processing electronic health record (EHR) data for clinical informatics tasks [18–20] compared to traditional methods, and has shown better performance with less processing time before learning and feature engineering [21]. Some deep learning algorithms have been approved by the FDA (Food and Drug Administration, USA), enabling the public to manage their health more effectively. Thus, in 2017, an algorithm for smart watches that used photoplethysmography and accelerometer received FDA approval to detect atrial fibrillation, and later in 2018, this approval was implemented in the Apple Watch Series [8]. These devices learn to measure the user's heart rate at rest and during physical activity, and are equipped with tactile alerts that will record ECG changes with the watch when a significant abnormality is detected. AI-powered smartphone apps for medical compliance and diagnostics, including the detection of skin blisters and rashes, ear infections, migraines, and retinal diseases such as diabetic retinopathy and age-related macular degeneration, are developing rapidly. The *AiCure* app (NCT02243670) requires a patient to videotape themselves swallowing a prescribed pill. Other apps use food image recognition to determine caloric and nutrient content, and with multimodal data, AI provides personalized nutrition recommendations and enables personalized health coaching and monitoring. Dating apps between doctors and patients have also been upgraded to provide a higher level of trust.

3.1. Diagnosis and monitoring of diseases. AI can help in the detection and diagnosis of various diseases. It can analyze clinical data, images, laboratory results and other medical parameters to help doctors make a diagnosis. For example, recent studies have shown the successful use of AI in the diagnosis of skin cancer, breast cancer, and other diseases [22].

Doctors need to understand the genetics of diseases in order to choose treatments and provide more accurate diagnoses. However, medically relevant differences in patient genomes require prediction of the pathogenicity of mutations, which requires characteristics such as protein structure and evolutionary conservation for learning algorithms to function. Deep learning (DL) techniques, with their greater power and ability to efficiently process different types of data, will likely yield more accurate predictions of pathogenicity than is possible today. Machine learning (ML) makes phenotype predictions using genetic data, including disease risks. Deep learning (DL) with additional data, such as medical images, clinical history, and data from handheld devices, can improve such models. Deep learning, as an improved version of machine learning, together with large repositories of medical data and advanced learning algorithms, supported by doctors, has now reached a higher level than before, including image analysis, language processing, information retrieval and prediction. With the help of deep learning algorithms with models that are constantly trained and updated on real clinical data, future doctors are able to make accurate diagnoses and individually optimized treatment decisions [23, 24].

AI can be used to continuously monitor the state of patients and detect changes that may indicate deterioration of health or the risk of developing complications. The use of AI in monitoring can help detect problems early and provide recommendations for further treatment. The use of artificial intelligence (AI) and body sensors is an integral part of Internet of Things (IoT) technologies. As a result of the rapid development of artificial intelligence methods, healthcare professionals have gained a greater opportunity to work with huge amounts of data that are collected with the help of wearable devices to monitor the health of patients. Artificial intelligence improves the ability to explore the relationships between information obtained from sensor signals and people's health by establishing different types of diagnostic and predictive models. The use of artificial intelligence in the processing of body sensor data is extremely important for optimizing the diagnosis and prediction of cardiovascular diseases.

3.2. Development of individual treatment plans. AI can analyze patients' medical data and recommend individualized treatment plans. It can take into account factors such as medical history, genetics, drug reactions and other factors to help doctors prescribe the optimal treatment for a particular patient. The application of artificial intelligence (AI) methods in the processing of large volumes of data is developing very quickly both in clinical practice and in everyday life. The popularity of wearable devices such as smart watches is growing rapidly. A variety of home tests, including digital glucose tests, blood pressure tests, and genetic testing, allow people to take control of their health by connecting to different consultations on different websites. Thus, patients already have their own daily records of their health long before they see a doctor.

More advanced clinical applications include image analysis that can identify skin cancers with the same accuracy as trained dermatologists. In July 2018, the world's first autonomous diagnostic system based on artificial intelligence was launched in the United States to detect diabetic retinopathy, a severe complication of diabetes that, without proper monitoring and treatment, can lead to complete vision loss. The developer of the system, the IDx company, has developed its own algorithm for diagnosing retinopathy in adults aged 22 years and older with diabetes using fundus images. The University of Iowa became the first healthcare organization in the United States to introduce the technology into clinical practice.

3.3. Improving the management of medical resources. AI significantly helps in optimizing the allocation of medical resources such as doctors, beds and medical equipment. It can analyze data on demand for services, forecast workloads and recommend more efficient allocation of resources to ensure quality health care. Artificial intelligence (AI) can play an important role in improving healthcare resource management.

AI can analyze large volumes of data about patients, medical records and other factors that affect the demand for health services. Based on this analysis, it can predict future demand and help managers of medical facilities plan the allocation of resources. AI can take into account a variety of factors, such as the number of patients, types of services and staffing needs, to help optimize the scheduling of medical staff. It can take into account the workload, ensure the right number of employees in different departments and ensure efficient use of resources.

AI can analyse medical data to identify patterns and anomalies that may indicate inefficient use of resources. For example, it can detect excessive use of certain services or identify areas where more resources are needed. AI can analyze patient data, such as medical histories, risk factors, and prescriptions, to predict the risks of certain diseases or complications. This can help healthcare facility managers develop effective resource plans to ensure optimal treatment and risk management.

AI can automate many routine tasks and processes, freeing up medical personnel's time for more complex professional tasks. It can also help healthcare facility managers identify and optimize resource spending, reducing overhead and improving efficiency. The use of AI to improve the management of medical resources can lead to reduced costs, increased efficiency and improved quality of medical services. However, it is important to remember the ethical and confidential issues related to the processing of medical data and the use of AI, and take them into account when implementing these technologies in medical institutions [23].

3.4. Bringing GenAI to healthcare. *Generative artificial intelligence* (GenAI) describes algorithms (such as ChatGPT) that can be used to generate new content, including audio, code, images, text, simulations, and video [25, 26]. GenAI is a free chatbot that can generate an answer to almost any question. It can take unstructured data sets – information that hasn't been organized according to a pre-set pattern, making the data difficult to process – and analyze it, making it a potential breakthrough for healthcare operations that are rich in unstructured data, such as clinical notes, diagnostic images, EHR. Instead of having a nurse or doctor write down information (from vital signs to treatment plans), GenAI can listen to the conversation during an appointment and create a summary that can be added to the EHR instead of manual data entry with potential for errors. In addition, such technology can also simplify the complex medical language in this summary so that patients can understand its content. That is, GenAI can transform unstructured data sets (such as clinical notes, diagnostic images, medical charts and records) into structured ones, which represents a potential breakthrough for healthcare operations.

GenAI provides the opportunity to reimagine much of the healthcare industry in a way it hasn't seen to date with previously available technologies (Fig. 4).

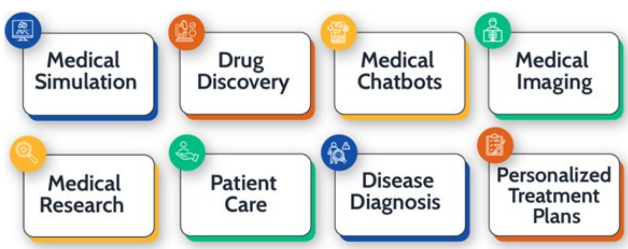

Fig. 4. Top GenAI Use-Cases in healthcare [26]

Today, it is being actively tested by hospitals and clinics in everything from automatically entering the results of doctor-patient contacts into the EHR of the latter to suggesting changes in documentation and providing relevant treatment and decision support services. Some health systems have already integrated this system into their operations as part of pilot programs. Once GenAI reaches maturity, it will also be able to integrate with other emerging technologies such as virtual and augmented reality. to transform the procedures for the provision of medical services.

3.5. Integration of SOA and AI. The integration of artificial intelligence (AI) and service-oriented architecture (SOA) opens new opportunities in various fields, particularly in healthcare, allowing healthcare systems to improve decision-making, improve patient care and optimize the use of resources. The rapid proliferation of IoT devices in healthcare has led to the creation of huge databases that require intelligent systems to analyze and extract meaningful information. By integrating AI capabilities into existing SOA infrastructure, healthcare organizations can harness the power of predictive analytics, machine learning, and natural language processing.

The combination of SOA and AI provides numerous benefits, including:

– *Enhanced decision-making capabilities* with AI-powered analytics and insights.
– *Increasing work efficiency* thanks to the automation of solving complex tasks and optimizing the use of resources.
– *Real-time monitoring* and proactive management of systems and services.
– *Personalized services* and recommendations based on individual user's data and preferences.

But the integration of SOA and AI requires a preliminary solution of several tasks, such as ensuring:

– *Data quality and standardization*: ensuring consistency and accuracy of data across various AI services and components.
– *Interoperability*: establishing seamless communication and interaction between AI and SOA components.
– *Algorithm Transparency*: creating AI algorithms that can be interpreted and explained in terms of regulatory compliance and ethical considerations.
– *Scalability and performance optimization*: managing the increased computing requirements of AI algorithms within the existing SOA infrastructure.

Additionally, the integration of AI and SOA raises security and privacy concerns, especially in healthcare where sensitive patient data is involved. AWS, as noted earlier, provides a robust cloud platform for deploying microservices that facilitate the integration of AI into existing SOA frameworks using AWS Lambda, Amazon API Gateway, and Amazon ECS (Elastic Container Service). At the same time, it is possible to create scalable, modular microservices that can work both individually and in various combinations depending on the user's rights in the system. This architecture enables independent deployment and scaling of AI-based services, facilitating integration with existing SOA components.

Data flow is a critical aspect of the integration process. The diagram (Fig. 5) shows the flow of data between AI components and SOA services in a typical integration scenario.

To isolate the transfer of sensitive information and prevent cloud storage of de-anonymized data, it is suggested to break the architecture into loosely coupled layers with strong cohesion within each layer. This approach forces the user to partially process private data at the edge of the infrastructure and provides only aggregated and anonymous data to the cloud storage system. The system consists of the following levels, as shown in Fig. 6.

The expert level is a doctor chosen by the patient who is able to prescribe treatment by approving the recommendations of the level of analysis.

The cloud layer is capable of data collection, storage, analysis and integration with external data. Although it is scalable, cost-effective, and provides easy access to information, it is highly vulnerable to most types of denial-of-service (DDOS) attacks and human-targeted hacking.

ISSN 2664-9969

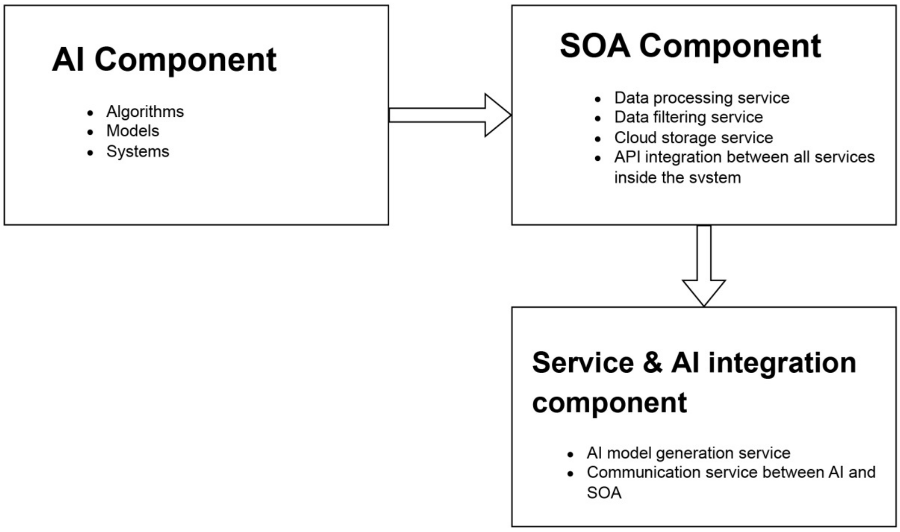

Fig. 5. Data flow in the AI and SOA integrated system

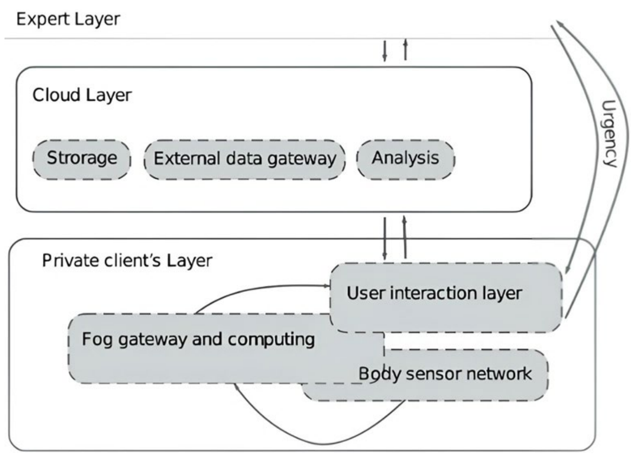

Fig. 6. Proposed system levels and groups of services

The level of the private client, consisting of the level of body sensors (Body Sensor Network, BSN), fog computing and cloud gateway (Fog gateway and computing) and the level of interaction with the user (User Interaction). These sub-layers are able to process sensor output and obtain context, integrate with the cloud, and provide feedback to the patient [23].

A user's smartphone is typically used as *a cloud gateway* because it provides cloud-level Internet connectivity and Bluetooth to communicate with sensor networks, coupled with sufficient computing power to process the data, and it is always aware of the user's location and other contextual data. Basic data collection and processing is performed on smart sensors, which reduces network load and eliminates security and privacy concerns. Moreover, modern smartphones can even participate in the analysis process.

3.6. Challenges and prospects. The paper examines the application of artificial intelligence and SOA together with the medical Internet of Things (IoT) and the Amazon Web Services (AWS) cloud to improve diagnostic accuracy, real-time patient health monitoring, personalized treatment and proactive healthcare management.

Key considerations and challenges of AI and SOA integration, such as data quality, interoperability, algorithm transparency, and scalability, are also covered. Cloud systems provide a full suite of services that address these challenges by offering robust security measures, scalability options, and data integration capabilities.

However, it is important to recognize that the integration of AI and SOA requires the investigation and solution of certain problems of data standardization and their compatibility, transparency of algorithms, and ethical considerations by the joint efforts of doctors, lawyers, and architects of information systems. Cooperation between stakeholders, compliance with regulatory guidelines, and continuous progress in IT technologies are critical to the successful implementation of the next stage of medical reform in Ukraine.

The country's healthcare organizations will be able to use the full potential of the medical Internet of Things, which will lead to a significant improvement in the results of patient treatment, optimized use of resources, and enrichment of the medical experience. The integration of AI and SOA paves the way for a smarter, more efficient, and patient-centric healthcare ecosystem.

4. Conclusions

The research summarizes the possibilities of integrating neural networks and artificial intelligence as services into a single e-Health system built using SOA architecture. The main idea is to develop a unified approach to the design of a complex of software applications with the involvement of methods of intelligent daєta analysis, which increases the efficiency and reliability of application software, and the use of ontologies of the subject area contributes to the dynamic integration of services from different developers into a single service environment. This will make it possible to develop a platform for collecting and analyzing medical data, as well as to develop a unified framework that will help in the future to integrate the application with other solutions that already exist on the e-Health market.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

Financing

The research was performed without financial support.

Data availability

The manuscript has no associated data.

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