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CONTENT

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Intelligent Control of Microgrid System: A Short Review

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Abstract: Microgrids combine distributed generation, storage, flexible loads, and local intelligence into a single operational layer, making it one of the essential building blocks of resilient low-carbon power systems. The control problem they face is inherently multi-time-scale and multi-objective, like converter-level dynamics, which must be stable at the millisecond level; frequency and voltage need to be restored in seconds, but economic dispatch and connection with the grid need minutes to hours for optimization. In this mini-review, authors summarize the latest status and challenges of intelligent microgrid control, where emphasis is placed on adaptive control, model predictive control, distributed and multi-agent control, as well as fuzzy-neural methods and reinforcement learning.

Keywords: intelligent control, model predictive control, adaptive control, multi-agent systems, energy management

1. Introduction

A microgrid can be defined as a localized energy system utilizing distributed energy resources, storage units, controllable loads, and supervisory control to operate grid-connected or in islanded mode. At the technical level, microgrids are green because they improve resilience, host renewable generation, can help reduce network congestion, and enable electrification on campuses, communities, industries, and remote sites. However, these advantages come with rigorous requirements for control. Renewable generation is intermittent, storage devices have state-of-charge limits, loads are partially stochastic, and inertia-dominated networks exhibit fast dynamics. Hence, microgrid control is not a single-loop but a layered decision problem involving converter control, system restoration, economic dispatch, protection coordination, and secure communication [1], [2], [3], [4].

Conventional droop and proportional integral (PI) based control are primary, but the rapid increase of distributed sensing, computation, and data availability brings more research interest in intelligent control. In this review, authors consider intelligent control in its broadest sense as methods that adapt to uncertainty and take advantage of prediction, coordinate distributed agents, or learn from data. That is the adaptive and robust control, model predictive control (MPC), distributed multi-agent coordination, fuzzy-neural control, or reinforcement learning topics [2], [4], [5].

2. Microgrid Architecture and Control Hierarchy

Almost all real-world microgrids are hierarchically structured. Primary control is exercised at the level of the converter (primary level) to achieve stabilization of voltage, frequency, current, and power-sharing within a timescale of milliseconds. Secondary control aims to reinsert the deviations that droop control introduces purposefully, and to schedule voltage or frequency correction over larger time scales. Tertiary control is responsible for power exchange with the utility grid, economic dispatch, demand response, and market participation. Different algorithms fit different layers so that this slightly hierarchical view is still a useful conceptual backbone of intelligent control [1], [2],[4].

Droop control is still a dominant primary strategy for AC microgrids because it enables decentralized power sharing with minimal communication. DC microgrids, on the other hand, also use either current- or voltage-droop implementations. On the other hand, droop control leads to steady-state deviations and performs poorly as line impedance uncertainty, converter heterogeneity, and parameter mismatch grow. Consequently, the secondary control becomes essential to re-establish voltage and frequency, along with effective active and reactive power distribution. Tertiary control optimizes the microgrid even further against external prices, forecasts, emissions, reliability targets, and network constraints [1], [3].

The hierarchy, seen through the lens of intelligence, suggests a design specification in which the faster the loop, the more necessary explicit stability and real-time simplicity are endogenous, while at slower loops, a huge scope exists for prediction, optimization, and data-driven learning. This is why adaptive and robust controllers are particularly suited for primary layers, whereas MPC, distributed optimization, and learning-based policies become more feasible at the secondary and tertiary levels.

3. Intelligent Control Categories for Microgrids

The intelligent microgrid control can be broadly categorized into five categories. The first category consists of adaptive and robust controllers, which update parameters online or shape the closed-loop response against disturbances. These methods are particularly appealing for inverter interfaces because they maintain an intuitive control architecture while enhancing resilience to feeder changes, uncertain inertia, or renewable variability. Adaptive inverter control and frequency regulation techniques developed recently indicate that these schemes can outperform traditional fixed-gain methods in terms of dynamic operating conditions, especially when the PV systems and battery systems are closely coupled [6]. Intelligent control functions for a microgrid in a hierarchical view shows in Figure 1.

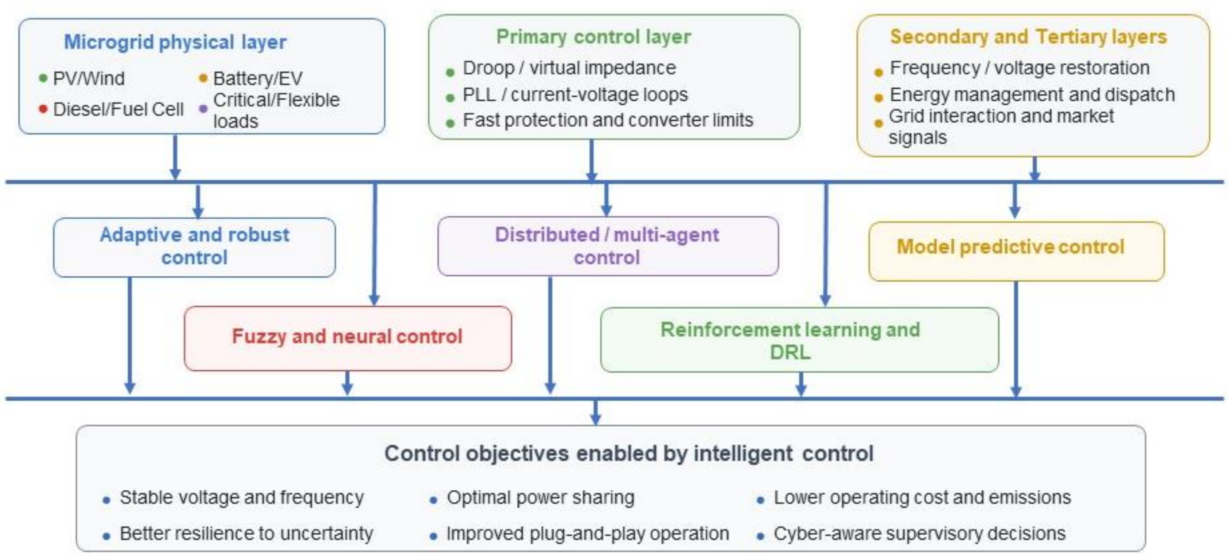

Figure 1. Hierarchical view of intelligent control functions in a microgrid.

The second part of the category will embrace the prediction and constraints handling in microgrid control from MPC and distributed MPC. They can jointly optimize many different variables, such as state-of-charge limits, power balance constraints, converter saturation and ramp-rate limits, in a receding-horizon formulation embedded with economic objectives. As the recent reviews illustrate, MPC has also emerged as one of the most developed intelligent-control approaches for microgrids, particularly with respect to converter control and energy management [7], [8]. The weakness is computational load, mis-specification, and the need for prediction accuracy. Distributed MPC partially solves scaling-up and personal privacy by decomposing the optimization problem on collaborative agents [9].

Third, due to the fact that microgrids are geographically distributed cyber-physical systems, methods for control based on distribution and multi-agent approaches will gain even more importance. Instead of centralization via a controller, agents communicate locally and arrive at consensus on frequency restoration, sharing power, or dispatch. While these methods enhance modularity and plug-and-play capability, they strongly rely on the assumptions of communication reliability, connectivity of the underlying graph, and resilience against malicious or delayed data [4], [10].

Fourth, fuzzy and neural approaches provide nonlinear mapping ability while requiring less computation online. Fuzzy logic provides a means to represent operators' knowledge when finding an accurate model is impossible, and neural approximators characterize nonlinear relationships between the state variables, disturbances, and control actions. These approaches are particularly common in load-frequency control, battery scheduling, and hybrid renewable coordination. It is not only raw performance with them, but their challenge also includes repeatability and stability certification, as well as generalization beyond the training envelope.

Fifth, RL and deep RL deserve much attention because they optimize sequential decisions with uncertainty without exact analytical models. Importantly, recent systematic reviews indicated that RL is being applied to dispatch, voltage regulation, demand response, storage scheduling, and fault-tolerant restoration [11], [12]. For instance, RL is an appealing technique in microgrids when the surroundings are stochastic with high dimensions. But real-world applications remain confined by sample efficiency, exploration safety, cybersecurity risk, and difficulty in establishing rigorous guarantees for stability or constraints satisfaction. Therefore, hybrid-based options like learning policies are enveloped with supervisory safety layers, model-based filters, or also MPC-style constraint shields seem to be the most viable direction [11], [13].

4. Energy Management, Resilience, and Cybersecurity

Intelligent control of microgrid is not only a converter-level issue but rather an energy-management problem. The recent future has challenged energy management systems to decide when to charge or discharge batteries, curtailment of renewable generation, shifting of flexible demand actions with the utility grid, and EV charge support. Subsequently, AI-enabled energy management became a hotspot of research. As AI techniques are trending in forecasting, dispatch, demand response, and resilience improvement at microgrids when EVs and storage are tightly coupled to the microgrid, recent reviews reveal that [5], [14].

A very interesting design challenge is the balance between optimality and interpretability. While deep models might enhance forecast quality or policy performance, operators need transparent decision-making for reliable, risk-compliant operation. This is the reason why a lot of practical architectures set forecasting AI upstream of optimization or rule-based control instead of replacing the entire end-to-end decision chain with an opaque policy. The other big challenge is transferability, i.e., a controller trained on one microgrid topology or climate profile may not work as well on another system. That is, digital twins and domain-adaptation strategies are gradually becoming keys to intelligent energy management.

Intelligent microgrid control links cannot be separated from cybersecurity, since the introduction of communication links, IoT devices, and distributed controllers increases the attack surface. Intelligent control may degrade by false-data injection, denial-of-service, and replay attacks, or compromise a dispatch decision via distributed agents, which in turn can destabilize restoration loops. In a review on cyber resilience in renewable microgrids [10], it was stated that, in the same way control performance is important, secure protocols, anomaly detection, resilient estimation, and standards-based design should also be at the forefront of research. For intelligent controllers, cyber resilience needs to be designed in, not bolted on. In particular, this allows for authenticated data flows, trust-aware state estimation, attack-tolerant distributed coordination, and safe islanded modes.

5. Comparative Analysis

As shown in Figure 2, the comparative analysis of intelligent control methods, no single method outperformed all microgrid layers actually. Adaptive and robust controllers are appealing for fast local loops due to their lightweight and easily certified nature, but have poor performance for long-horizon economic scheduling. MPC shows performed results when strict constraints and forecasts are in place, but efficacy depends on modeling fidelity and optimization resources. Multi-agent methods do scale well for distributed systems and alleviate the issue of sole reliance on a central controller. But they are also vulnerable to communication rate or quality and cyber threats. Fuzzy-neural approaches require moderate computational effort to model complex nonlinearities, while also posing more concerns in terms of tuning and interpretability. RL-based methods are effective for supervisory control in uncertain environments, but they need an aware safety design and reliable training data [4], [5], [6], [7], [8], [9], [11],[12], [13], [14].

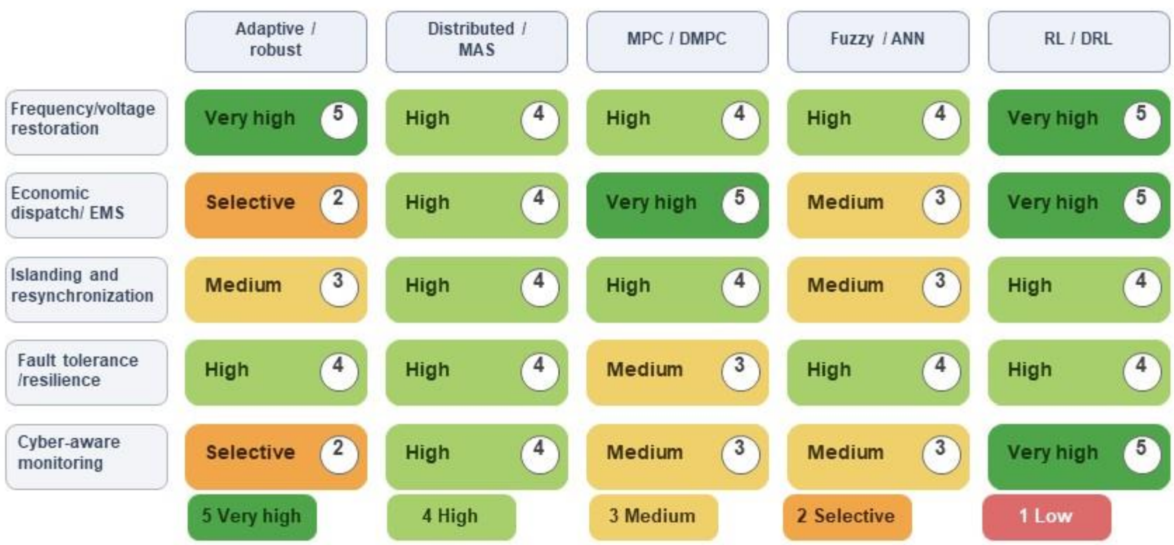

Figure 2. Relative suitability of intelligent control methods across key microgrid tasks.

The strongest trend in the recent literature is convergence rather than competition. Researchers increasingly combine forecasting AI with MPC, distributed consensus with reinforcement learning, or adaptive inner loops with intelligent supervisory layers. In other words, the field is moving toward architecture-level intelligence rather than a single algorithm replacing all others. For practitioners, the design question should therefore be: the level of the hierarchy is being controlled, the critical constraints, the existing communication infrastructure, and the safety requirements. These questions are more useful than the type of algorithm that is globally best. Table 1 shows the comparative analysis of the main intelligent control categories for microgrids.

Table 1. Comparison of major intelligent control categories for microgrids [1]-[14].

Method categories	Typical layer	Main strengths	Key limitations	Data dependence	Best-fit applications
Adaptive/robust	Primary/secondary	Fast response, parameter tolerance, and easier stability analysis	Needs careful tuning; less suited to long-horizon optimization	Low	Inverter control, frequency restoration
MPC/DMPC	Secondary/tertiary	Constraint handling, predictive dispatch, multi-variable optimization	Computational burden, forecast, and model dependence	Medium	EMS, storage scheduling, coordinated converters
Distributed/multi-agent	Secondary/tertiary	Scalable, modular, plug-and-play, privacy-preserving	Sensitive to communication quality and cyber attacks	Medium	Consensus restoration, peer-to-peer coordination
Fuzzy/neural	Primary to tertiary	Handles nonlinear behavior with moderate online cost	Interpretability and certification challenges	Medium to high	Load-frequency control, hybrid renewable coordination
RL/DRL	Secondary/tertiary	Learns sequential decisions under uncertainty; strong for stochastic environments	Safety during exploration, sample efficiency, trustworthiness	High	Dispatch, EV charging, resilience-oriented supervision

6. Future Research Directions

The next phase in intelligent microgrid control is likely to fall into three directions. The first is hybridization. Purely model-free learning remains risky for safety-critical power systems, while purely model-based control struggles with uncertainty and adaptation. Hybrid controllers that fuse state estimation and prediction with responsive, robust fallback logic and learning-based policy improvement are also more applicable in practice.

The second is edge intelligence. Microgrid controllers have been implemented on embedded devices that are close to converters, meters, and protection relays. It means using small models, communication triggered by events, and an inference mechanism stable under latency and packet loss. As such, intelligent control needs to be co-designed with hardware constraints instead of being evaluated solely in cloud-scale simulations.

The third is around standardized benchmarking. One of the biggest challenges in advancing RL and DRL is that many studies differ greatly in modeling, cost functions, cyber assumptions, and measures used to evaluate these frameworks. Joint evaluation of voltage or frequency quality, state-of-charge health, economic cost, resilience, and cyber robustness would create a field that is much more cumulative (see Table 2). Particularly in the case of RL and AI controllers, such benchmarks are critical as reported benefits can vary significantly by scenario [10], [11], [12]. For this purpose, Table 2 shows design guidelines to choose intelligent control methods.

Table 2. Design guidelines for selecting intelligent control methods [10]-[12].

Design requirements	Recommended emphasis	Why	Avoid relying on only
Hard constraint handling and dispatch optimality	MPC/DMPC	Explicitly manages limits, forecasts, and multi-objective costs	Pure droop or untuned heuristic rules
Plug-and-play coordination across many Distributed Energy Sources (DERs)	Distributed/multi-agent control	Improves modularity and reduces central bottlenecks	Single-point centralized logic without redundancy
Fast, certifiable local regulation	Adaptive/robust control	Fits converter-level loops with lower computational burden	Heavy learning models in the innermost loop
Operation under strong uncertainty and complex sequential decisions	RL/DRL with a safety layer	Learns policies for stochastic environments and supervisory actions	Unconstrained model-free learning without safety envelopes

7. Conclusion

Modern microgrids most heavily rely on intelligent controls due to fast local stabilization and slower supervisory intelligence, both required for renewable-rich, inverter-dominated systems. The literature demonstrates that while classical hierarchical control is still the organizing paradigm, intelligent techniques are ever more augmenting each layer. For example, adaptive and robust control enhance converter-level resilience, model predictive control promotes constrained decision making, scalable multi-agent architectures improve scalability through distributed solutions, fuzzy-neural systems produce better representations of nonlinear behavior, and reinforcement learning supervises controls under uncertainty. Replacing classical control is not the most credible path forward, but rather providing model-based guarantees combined with learning-based adaptability. The most effective intelligent control for microgrids will apply algorithms that are not selected simply by what is new, but appropriately mapped to layer, operating constraint, communication context, and safety requirement.

Author Contributions

Both authors reviewed and approved the final version of the paper.

Conflict of Interest

The authors declare no conflicts of interest.

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Smart Homes: Energy Efficiency and Safety Issues

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Abstract: This article comprehensively examines energy efficiency and security issues in today's rapidly evolving smart home technologies. As a result of the adoption of new technologies such as digitization, automation, and the Internet of Things (IoT), significant achievements have been made toward optimizing energy use, enhancing security, and managing resources in residential buildings. Smart home systems not only provide home comfort but also prevent energy waste, reduce environmental load, and serve sustainable development goals. The article extensively analyzes the structural principles of smart home technologies, energy management mechanisms, the role of artificial intelligence (AI) and cloud technologies, as well as information security and cybersecurity issues. In the global experience, the application of smart home systems in the USA, Japan, Germany, and Scandinavian countries has resulted in 15-30% savings in energy consumption. In addition, the article examines the ways of localization of these experiences for Azerbaijan, state programs, and development directions of the normative-legal framework. The study shows that widespread adoption of smart home systems contributes to both energy independence and environmental sustainability. However, increasing network connections, the proliferation of IoT devices, and cloud-based data processing processes are creating new cybersecurity risks. For this reason, the article emphasizes the importance of implementing information security standards (ISO/IEC 27001, GDPR, etc.) in addition to ensuring technological efficiency. In general, the research aims to determine the scientific, technological, and social aspects of smart home models that increase energy saving, security level, and user well-being, as well as to evaluate the development prospects of this field in the conditions of Azerbaijan.

Keywords: smart home, energy efficiency, cybersecurity, IoT, AI, environmental sustainability, green energy, digital transformation

1. Introduction

The 21st century is characterized as an era where the global energy crisis and digital transformation intersect. Growing energy demand, climate change, urban congestion, and limited natural resources force humanity to look for smarter and more efficient technological solutions [1]. If the 20th century was the period of the industrial revolution, the 21st century can be evaluated as the stage of "digital and energy revolution". At the center of these changes is the concept of "smart home" - it is not just a technological innovation, but also a key component of social and environmental transformation. Smart homes connect home equipment, devices, and systems through information and communication technologies, optimizing energy use and providing user comfort [2]. These systems automatically manage heating, lighting, security, household appliances, and even water resources. Thus, the need for human intervention is minimal, energy losses are reduced, and the quality of life is increased. According to UN data for 2024, 35% of the world's energy consumption is accounted for by residential buildings, and 28% of carbon emissions are formed in this sector [3].

This fact shows that the efficient use of energy is not only an economic issue, but also an issue of environmental and social responsibility. The modern approach is that the "living space" is not only a space, but also an "intelligent system" that collects information and saves energy. The government of Azerbaijan has also taken a number of steps in this direction. "Green energy" policy, "Smart city" and "Smart village" projects, especially the "Green Zone" initiatives in Karabakh and Eastern Zangezur, represent an important turning point in the country's energy and technological policy [4]. These projects ensure not only technological modernization but also environmental protection, energy security, and the implementation of a sustainable development strategy.

2. Smart Home Concept and Technological Basics

The technological infrastructure of smart homes is mainly based on the Internet of Things (IoT), artificial intelligence (AI), sensor technologies, cloud services, and automated control systems [5]. These systems operate at three interconnected levels and collect and analyze data in real time.

Physical level: At this stage, data is collected through various sensors and devices. Temperature sensors, motion detectors, light sensors, energy monitoring devices, and security cameras monitor the activity of the house. For example, a temperature sensor adjusts the temperature according to weather changes, a motion sensor turns off the lights when no one is in the room, and an energy monitoring device monitors consumption. Thanks to these technologies, energy consumption is reduced to a minimum, and the level of comfort increases.

Network layer: Data is transmitted through IoT communication protocols (ZigBee, LoRaWAN, MQTT, Z-Wave). ZigBee provides short-range communication with low power consumption, while LoRaWAN is suitable for longer distances and finds wide application in rural areas. The MQTT protocol allows reliable data exchange with low bandwidth. Thanks to these systems, all devices in the house can be connected to a central control panel or mobile application.

Cloud layer: Cloud technologies process the collected data and analyze it with AI models. For example, by looking at the user's energy consumption history, the system can suggest new settings for energy saving. Cloud services also enable remote control: the user can monitor and control their home from anywhere in the world through a mobile application [6].

The role of artificial intelligence: Artificial intelligence and machine learning algorithms analyze user behavior to ensure optimal energy management. For example, the system learns the time the user leaves the house every day and automatically reduces the heat, thus reducing energy consumption by up to 25%. AI also optimally adjusts the indoor climate, taking into account weather forecasts. International experience shows that households saved 15% annually on gas and electricity due to the application of the "Nest Learning Thermostat" in the USA [1]. In Europe, Smart Grid technologies have reduced energy loss by 10-12% by balancing energy distribution [7]. As a result of the "E-Energy" project implemented in Germany, energy efficiency in buildings has increased up to 40%. In the reality of Azerbaijan, the implementation of these systems is taking place gradually. The smart meter system implemented by "Azerishiq" OJSC facilitates the monitoring of energy consumption and prevents illegal use [6]. Smart lighting, heating, and security systems are installed in new residential complexes in the capital and regions, which serve to save energy and improve the quality of life.

3. Energy Efficiency and Management Mechanisms

Energy efficiency is one of the main indicators of environmental and economic stability. The International Energy Agency (IEA) states that by 2030, the implementation of intelligent management systems in buildings can reduce global energy demand by 10% [1]. Energy management in smart homes is formed in four main directions:

Real-time monitoring: Smart meters monitor energy consumption on a second-by-second basis and provide graphical and analytical information to the user. This information increases the transparency of energy behavior and encourages users to save. For example, according to a study conducted in Great Britain, energy consumption was reduced by an average of 18% in homes with a real-time monitoring system installed [1].

Adaptive control: Sensors automatically adjust devices based on indoor temperature, light, and motion [5]. For example, when there is no one in the room, the lights turn off, the curtains close automatically according to the angle of sunlight, and the air conditioner switches to the optimal mode. This process reduces energy consumption and saves electricity costs.

Renewable energy integration: Solar panels, wind turbines, and battery systems are integrated into smart homes [4]. These systems balance energy production, storage, and distribution. Already produced energy can be transferred to the grid or stored in a "home energy bank". In Japan's Panasonic Smart Town project, houses consume 30% less energy per year [3].

Analytical forecasting: AI systems predict future demand by analyzing past energy data, weather forecasts, and usage patterns. It plays an important role, especially in "dynamic regulation of energy price" systems [1].

Houses built on the basis of the "Net Zero Energy" concept in Scandinavian countries produce their own energy and transfer excess energy to the network [7]. Denmark and Sweden are already building "energy positive" buildings, meaning they produce more energy than they consume. For Azerbaijan, these approaches are of strategic importance for the future. In particular, the Nakhchivan and Karabakh regions have high potential in terms of solar energy [4]. The implementation of "greenhouses" and "energy independent villages" projects here is appropriate both from the economic and ecological point of view.

4. Cybersecurity and Data Protection

In addition to the widespread use of smart home systems, information security issues are becoming more and more relevant [8]. The proliferation of IoT devices makes home networks a potential target for cyberattacks. According to the US Cyber Security Agency's 2023 report, 46% of smart home devices have experienced a cyber threat at least once [7].

An in-depth analysis of key cybersecurity risks in smart homes. Although the technologies applied in smart homes make everyday life easier, these systems also create new cybersecurity challenges. The main risks are: weak authentication mechanisms, delay of firmware updates, poor protection of home routers, data leakage in cloud services, and unauthorized connection of devices to the network [9]. Each of these problems should be analyzed from both technical and user behavioral perspectives.

The main risks are:

Weak authentication mechanisms and duplicate passwords

Most smart home systems are equipped with simple and identical passwords during the initial installation phase. For example, many devices store default passwords such as "admin/admin" or "12345". Since most users do not change these passwords, cybercriminals can easily access home systems using this publicly available information [6].

Weak authentication mechanisms are not only related to password simplicity, but also to single-step authentication. If the system does not implement two-factor authentication (2FA), it is almost impossible to prevent cyber attacks.

Attackers use methods such as "credential stuffing" (that is, testing the same passwords on different systems) and "brute-force" (breaking passwords with force). According to a report by Bitdefender in 2023, 45% of attacks on IoT devices were due to password vulnerabilities.

Solutions:

- Strengthening the password policy (at least 12 characters, a combination of letters, numbers, and special characters);
- Application of two-factor authentication (2FA);
- Compulsory change of initial passwords of devices;
- Automatic login blocking (on repeated unsuccessful login attempts).

In the reality of Azerbaijan, awareness among users in this field is still weak. A 2024 report by the Ministry of Energy and Digital Development notes that 68% of users use the same password for multiple accounts on smart devices. This is a serious source of risk.

Delay of firmware updates

Firmware is the software that runs inside the device. Updating this software is important for both functional improvement and security. But many users and some manufacturers do not pay due attention to firmware updates. As a result, vulnerabilities in older versions become an open door for cybercriminals.

As a result of the delay in firmware updates, attacks such as "remote code execution", "data exfiltration", and "botnet connection" occur. For example, in 2016, an attack called the Mirai Botnet connected thousands of vulnerable IoT devices to launch one of the world's largest DDoS attacks. The reason for this attack was outdated firmware and unmodified passwords.

Measures to reduce risks:

- Activating the automatic update mechanism;
- Follow manufacturers' safety notices;
- Providing devices with original firmware (avoid fake versions).

Using reliable servers for updates. The Cyber Resilience Act has been adopted in the European Union since 2022, and according to this law, all manufacturers must provide firmware updates for at least 5 years. It is important to apply such requirements to the devices sold on the Azerbaijani market.

Weak protection of home routers

Home routers are considered the "gateway" of the smart home ecosystem. All smart devices access the internet through this network. When a router is poorly secured, the security of the entire system is compromised. The most common problems:

- An unencrypted “HTTP” interface is used during installation:
- Remote access to the router's control panel remains open;
- Instead of WPA2, the old WEP encryption standard is used.

Firmware updates are not performed. Cyber attackers can use these vulnerabilities to intercept data flows and download malware to devices through man-in-the-middle attacks.

Precautions for safety:

Activation of WPA3 encryption;

Changing the router's default management ports;

Disabling the "Remote Management" function;

Keeping the firewall function active;

Regular checking of router logs.

The US Federal Communications Commission (FCC) has set minimum security requirements for home networks in 2023. These requirements can also be applied in Azerbaijan, especially in newly built "smart housing" projects; manufacturers should be obliged to fulfill these technical norms.

Data leakage in cloud services

Cloud systems play the role of the "brain" of smart homes, because all data (temperature, camera images, energy consumption, user behavior, etc.) is collected here. However, if data protection is not ensured in cloud-based services, large-scale data leaks can occur. The most observed risks:

- Weak encryption of cloud servers;
- Transfer of information to third parties;
- Improper setting of access control;
- Absence of "TLS" (Transport Layer Security) use in device-server connection.

For example, in 2022, as a result of a vulnerability discovered in the cameras of the "Eufy Smart Camera" company, it was possible for third parties to watch user videos. This incident showed that cloud systems, however convenient, require a high level of security.

Solution directions:

- Data encryption at AES-256 or RSA-2048 level;
- "Zero-knowledge" model (only the user can see the information, not the server);
- Data storage on regional servers (in Azerbaijan or the EU);
- Personal data processing according to GDPR principles [9].

In the context of Azerbaijan, it is planned to prepare technical standards on cloud security for state bodies and the private sector within the framework of the "Digital Development Strategy" starting from 2024. This will increase the reliability of smart home services.

Unauthorized connection of devices to the network

Multiple IoT devices can create hundreds of connections in a home network. If these connections are left unattended, cyber attackers can enter the system through "unauthorized access". In particular, home cameras or smart doors can be hacked through "default" open ports (e.g., 23/Telnet and 554/RTSP). The most commonly used attack methods:

- MAC spoofing: An attacker presents their device as a genuine device. Evil twin attack: Deceiving the user by creating a fake Wi-Fi hotspot.
- Device cloning: Access to the system by creating a new device with the same identifier.

Recommended countermeasures:

- Network segmentation - Allocating separate Wi-Fi and VLANs for IoT devices;
- Access control (Access Control Lists - ACL) application; • Track MAC addresses of devices;
- Create a blocking policy for automatically unknown devices on the network.

For example, in South Korea, real-time network monitoring systems are implemented for all smart homes within the framework of the "Smart Home Security Framework". This system immediately detects suspicious connections and sends an alert.

Standardization and international practice

- It is important to apply international standards to prevent these dangers.

- ISO/IEC 27001 - international norm on information security management system; •ISO/IEC 27701 - additional standard on personal data protection;
- NIST Cybersecurity Framework - risk-based approach and action plan;
- GDPR (EU) - principles of legal protection of personal data and transparent processing.

It is important for Azerbaijan to adopt these standards at the national level, prepare the local "Smart Home Security Guideline" document, and hold awareness programs.

Human factors and education

No matter how advanced technology is applied, the human factor is still the weakest link. According to statistics, 70% of users do not change their device's default passwords, and 60% postpone software updates [6]. For this reason, in addition to technical measures, it is also important to form the knowledge and habits of users.

Users should be encouraged to behave safely through awareness campaigns, public social ads, and automatic alerts in mobile applications.

Although these issues are new for Azerbaijan, within the framework of the "Digital Development and Transport Strategy (2022-2026)", the creation of a cybersecurity ecosystem and the improvement of the "CERT.AZ" system have been identified as priority directions [4].

Cybersecurity is not only a technological issue, but also an ethical one. Smart home devices record user behaviors, voices, and even movement patterns. Sharing this information with third parties raises concerns for individual liberties and privacy [9]. Therefore, both the government and the producers must follow the principles of transparency in the collection and use of data.

5. The Role of Artificial Intelligence and Automation

Artificial intelligence (AI) is the basis of the management system of smart homes [5]. AI learns behavioral patterns by analyzing data collected from devices, adjusts energy balance, and ensures safety.

AI-based technologies:

Predictive energy management: The system predicts future energy needs [3]. For example, a system that predicts whether the weather will be cloudy allocates solar energy resources more efficiently.

Security: Performs facial recognition, voice recognition, and motion analysis [8]. The system learns the faces of the residents of the house and gives signals about strangers. At the same time, it can detect unusual sounds (for example, the sound of breaking glass).

Voice control: provides human-machine interaction through the Google Assistant and Amazon Alexa systems [1]. These systems not only execute commands, but can also understand context and provide personalized responses. Automatic fault detection: AI algorithms detect device faults in advance and send alerts. For example, the system notifies the user when there is a pressure drop in the boiler system, an overheated electric cable, or a leak in the water system.

In countries such as Singapore, Korea, and the UAE, AI-based Smart Nation programs are implemented at the state level [7]. All residential buildings in Singapore are equipped with smart energy management systems, which have increased energy efficiency by 25%. For Azerbaijan, it is appropriate to create specialties in universities and promote "startup laboratories" in the direction of AI application [10]. In particular, it is important to develop AI solutions for local conditions, as climate, culture, and user behavior differ across regions.

1. State policy, regulatory framework, and local practice.

2. The "Law on Energy Efficiency" adopted in the Republic of Azerbaijan in 2022 opened a new stage in energy management [4]. The law makes the energy audit and certification process mandatory.

State programs - "Green Energy Zone," "Smart City and Village Concept" - support technological transformation. "Smart grid" systems are being tested in the pilot projects implemented by "Azerishiq" and "Azerenergy" [6]. Intelligent lighting and energy management modules are applied in Ganja and Sumgait. Street lighting in these cities is automatically adjusted depending on the degree of darkness, resulting in a 30-40% reduction in energy consumption.

International cooperation is also important. The "Energy Efficiency 2030" project is implemented jointly with the World Bank and the UN Development Program [3]. Within the framework of this project, technical assistance is provided, training is organized, and pilot projects are financed to increase energy efficiency in Azerbaijan. In the future, the creation of a "green technologies fund" within the framework of the public-private partnership model can stimulate investments in this area. This fund can provide pilot loans, subsidies, and concessional loans for energy efficiency projects.

1. Social, environmental, and ethical aspects.

2. Smart home technologies are important in terms of social welfare and environmental sustainability [3]. For the elderly and physically challenged, these systems increase safety with voice control and emergency alarm functions [1]. For example, people with limited mobility can control the lights, curtains, TV, and open and close the door with voice commands.

From an ecological point of view, smart homes reduce energy waste and carbon emissions by up to 30% [3]. This also plays an important role in the fight against climate change. Smart homes help to use natural resources more efficiently - monitor water consumption, reduce waste, and optimize energy consumption. From a social point of view, these technologies change human behavior and encourage responsible use of energy [2]. Thanks to real-time monitoring, users directly see the results of energy consumption and tend to change their behavior. Ethical aspects are related to personal data processing [9]. Smart devices collect user habits and voices. Legal mechanisms are required for the proper management of these data [8].

Azerbaijan needs to adapt the "Law on Personal Data Protection" to international standards. In particular, the purpose of data collection, the storage period, conditions of sharing with third parties should be clearly defined. 1. Future perspectives and recommendations 2. In the future, smart homes will serve not only energy saving, but also social inclusion, health monitoring, and resource management [1]. In the next decade, smart homes will become energy-positive buildings, generate their own energy, and even provide power for electric cars. The health monitoring system will monitor the health status of the elderly and those suffering from chronic diseases, and will transmit information to doctors and relatives in case of urgent need for help.

6. The Secret to the Popularity of Smart Homes

The Internet of Things (IoT) is not just a fad. There are many factors affecting the growing popularity of smart home devices:

1. Rapid technological evolution. Hardware and software potential are developing every year. Current developments are different from what we knew before, which inevitably affects customer expectations and market transformations.

2. Emerging opportunities in cloud computing. Cloud infrastructure, which is indispensable for Internet of Things (IoT) solutions, is more accessible than ever. Smart home providers can benefit from flexible service options offered by popular cloud platforms such as AWS, Microsoft Azure, and Google Cloud.

3. Mandatory environmental standards. Many developed countries (smart meters) are incorporating smart home solutions into their environmental protection measures.

How to Connect Smart Home Elements?

There are four connection types:

- **Wi-Fi** is considered the most popular communication protocol for IoT devices. Since it is also the protocol that consumes the most energy, devices need to be charged regularly.
- **Bluetooth,** although less common than Wi-Fi, Bluetooth devices are cheaper and consume less energy. Its biggest disadvantage is low connection capacity. All IoT elements need to be positioned closer to each other, and users cannot control IoT systems outside the home.
- **Z-Wave**, It is a low-power consumption mesh network technology that provides high connection speed and allows adding any number of devices to the network. However, the Z-Wave signal only reaches up to 100 meters, so users cannot control their homes remotely.
- **Zigbee** is another affordable, low-power network technology used to connect smart home devices. Zigbee provides secure data transmission using 128-bit encryption keys and controls devices at a distance of 10-100 meters indoors. The Zigbee Alliance currently includes more than 600 companies (such as Siemens, Philips, Bosch, and others). This means that there are thousands of Zigbee-compatible devices, and their number is increasing every year.

7. Content of Smart Home Systems

Smart homes use advanced technology to make life more comfortable, create efficient housing facilities and daily family affairs management systems, and integrate facilities related to daily life. A smart home includes many types of home products; It serves users through smart communication, covering everything such as TV, bathroom, refrigerator, air conditioner, door lock, and other products. Smart home technology provides energy saving as well as security and comfort. Smart home systems will become more common day by day with the advancement of technology. These systems will provide benefits in terms of energy efficiency as well as advantages such as comfort, security, and time saving.

A complete smart home system is not just one device, but a combination of many home products with different functions. The user in a family consists of multiple users, not one person. The goal of smart home systems is to efficiently and intelligently coordinate home products and people into a unified system that can learn, connect, and self-adapt. Compared with interactive buttons and touch screens, voice assistant hardware is more convenient, and voice control has now become an important entry point for smart homes. The most important features of smart home systems are comfort, security, energy saving, and environmental friendliness. Home automation systems in smart homes are determined according to the needs of the people living at home, and the features of each smart home can be designed in a unique way. For example, the expectation of a smart home for disabled and elderly people in need of care is to ensure that health checks can be carried out and they can take their medications properly; the needs of a university student who wants to celebrate at home may include changing the sound system, video systems, and lighting of the house.

8. Healthcare Applications

Smart homes also have numerous applications in healthcare. They can be used to monitor the health and well-being of the inhabitants, particularly the elderly or those with chronic conditions. Devices like smart watches can track vital signs and activity levels, while smart cameras can detect falls or other emergencies. This data can be used to alert healthcare providers or family members in case of any abnormalities.

Furthermore, smart homes can facilitate telemedicine, allowing patients to consult with healthcare providers from the comfort of their homes. This can be particularly beneficial for those with limited mobility or those living in remote areas.

9. Future of Smart Homes

The future of smart homes looks promising, with advancements in technology and a growing awareness of the benefits they offer. As artificial intelligence and machine learning continue to evolve, the automation capabilities of smart homes are expected to become more sophisticated. This could lead to homes that can fully adapt to the habits and preferences of their inhabitants, providing a truly personalized experience.

Furthermore, as more and more devices become connected, the potential applications of smart homes will continue to expand. This could include everything from advanced healthcare monitoring to integrated energy management systems. However, these advancements will also bring new challenges, particularly in terms of privacy, security, and interoperability. Therefore, it will be crucial to address these issues to ensure the successful adoption of smart homes.

10. Use of Artificial Intelligence in Smart Home Systems

Table 1 illustrates the use of AI in smart home systems.

Table 1. Comparison of Artificial Intelligence Applications in Smart Home Systems.

Topic and Purpose	Technology and Feature	Result and Future Recommendation
Using deep learning to monitor daily nutrition [3].	Nutrition data are processed using Optical Character Recognition (OCR). Bayesian methods are used for classification.	A daily accuracy of 96.8% has been achieved. Integration with physiological monitoring systems is recommended to reduce errors and improve automatic diet tracking.
Monitoring system for elderly people using object tracking and sensor-based human-robot interaction in smart homes [7].	The system includes an assistive robot. ASUS Xtion Pro Live RGB-D camera integrated with a robotic wheelchair and a two-wheel robotic platform using BOSCH INDY5 IMU. Amazon Alexa and a deep learning architecture (DESA) are used.	Filtering techniques improve recognition accuracy. Integration with a comprehensive robotic assistant system is recommended.
Gamification system for sharing smart home data among family members and between families [11].	Motion sensors and environmental sensors collect data. GPU and DSP processors accelerate analysis.	Experiments show increased engagement through gamification, although some negative motivational effects were observed.
Detecting network anomalies in smart homes to monitor traffic problems and network security [12].	Machine learning methods detect unusual anomalies and prevent attacks in early stages. Data classification algorithms are applied.	Simulation results show that local anomalies can help identify suspicious network packets.
Using the Telegram application to control home entry-exit monitoring devices [12].	The Raspberry Pi camera module performs face recognition. Arduino and NodeMCU act as communication modules. Histogram and Binary Histogram algorithms are	The system allows monitoring people in front of the house camera. Performance depends on device speed, memory, and internet connection.
Testing artificial intelligence algorithms [13].	Sensor data coming from the smart home is transmitted through a gateway device to an MQTT server and stored in a MySQL database. The simulation process uses these recorded data. Software that enables this process is developed in JavaScript and designed to run in the Node.js runtime environment.	By modifying the simulation algorithm, the system can process real-time data collected from sensors. Artificial intelligence algorithms can be tested in different conditions in both real and virtual environments to evaluate their accuracy.
Examining the components of IoT-based smart home technologies, the motivation behind these technologies, the related issues, and the development of smart homes [14].	Communication protocols such as ZigBee, ZigBee Pro, ZigBee IP, low-power WPANs over IPv6, WiFi, Bluetooth Low Energy, RFID, and cloud computing technologies are used. CoAP, UDP, and HTML5 WebSocket	These components should be monitored and managed properly to ensure secure and reliable operation while reducing energy consumption under different conditions.

	communication protocols are also utilized.	
Customizing homes according to individuals' needs by using smart home decision mechanisms [15].	Integrated Decision Support Systems (IDSS) for smart homes, User-Centered Design (UCD), and Human–Computer Interaction (HCI) approaches are applied.	Future studies should focus on challenges such as sensor fusion, contextual awareness, uncertainty, and security issues in smart home technologies.
Efficient energy use and energy saving in smart homes using IoT-based devices and artificial intelligence [16].	SCADA systems are used to monitor and manage energy production units by different teams. Smart Electronic Devices (IED), mobile-based solutions, and Ethernet-based systems are also used.	IoT-based solutions are considered cost-effective. These hybrid solutions enable electrical energy to be managed efficiently.
Systematically reviewing smart home literature and evaluating the current situation from the perspective of users [17].	Artificial intelligence, sensors, and IoT technologies.	Future research should analyze consumer attitudes and preferences more comprehensively. Most existing studies have been conducted in England and the USA; therefore, future studies should focus more on Eastern countries to better understand the benefits and services of smart homes.
Evaluating new approaches for integrating sensors for applications such as identifying energy consumers and storage, human interaction, and developing wearable technologies using traditional micro-electromechanical system-based microsensors [18].	Triboelectric nanogenerators (TENG), nanogenerators (NG), artificial intelligence (AI), micro-electromechanical systems (MEMS), and High-Profile Bayes Point Machine Test (HPBMT).	Significant research has been conducted to further develop HMI, voice recognition, and IoT-based smart home control systems. Through micro-devices, smart interfaces, and skin-compatible wearable devices, new generation health monitoring systems capable of detecting physical and chemical signals have been proposed.

Recommendations:

- Promoting local "smart device" production: Developing local manufacturers will not only diversify the economy but also reduce dependence on foreign supply chains.
- Expanding energy audit and certification: An energy efficiency certificate requirement should be applied to all new buildings and old buildings undergoing major renovation.
- Applying national cybersecurity standards: Minimum security requirements for smart home devices should be defined, and compliance with these requirements should be made mandatory.
- Creating artificial intelligence centers: Centers specialized in AI research and application should be created in universities and research institutes.
- Formation of educational programs and curricula on smart home technologies: Specialties in the installation, management, and repair of smart home systems should be taught in vocational schools and universities.
- Security awareness campaigns for users: Users should be familiarized with safe usage rules of smart devices through mass media, social networks, and training seminars.

As a result of these measures, Azerbaijan could become one of the leading countries of a "green and digital economy."

11. Conclusion

Smart home technologies are one of the most efficient solutions responding to the energy, safety, and ecological challenges of the modern world. They play a crucial role in energy savings, creating a safe environment, and ensuring ecological sustainability [1].

For Azerbaijan, this direction holds strategic importance. The state's "green energy", "digital transformation", and "smart city" policies form a solid base in this field [4].

Successful results are possible not with the import of technology, but with the development of a local knowledge base, human resources, and security infrastructure [10].

In the future, smart homes will become one of the main infrastructure elements, ensuring not only energy savings but also social welfare, safety, and sustainable development [3].
The widespread dissemination of these technologies will be a step towards a cleaner, more efficient, and fairer energy future. Azerbaijan's active participation in this process will strengthen the country's energy independence, improve its ecological situation, and help increase citizens' quality of life.

Author Contributions

Shokrollah Ghadyani is solely responsible for the conceptualization, literature review, analysis, and writing of the manuscript, and approved the final version for publication.

Conflict of Interest

The author declares no conflicts of interest.

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A Secure and Intelligent IoT-Based Remote Patient Monitoring Framework for Early Detection of Alzheimer's Disease Using Edge AI and Federated Learning

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Abstract: Alzheimer's disease is a progressive neurodegenerative disorder and is widely recognized as a major burden on healthcare systems. Symptoms are often delayed; therefore, timely diagnosis is essential to improve patients' quality of life. However, traditional periodic clinical assessments may not accurately capture continuous changes in behavior and physiology characteristic of early-stage Alzheimer's. We present a secure Internet of Things (IoT)-based remote patient monitoring (RPM) framework. This model utilizes environmental and wearable sensors to collect physiological signals and behavioral data. Real-time data processing at the device level, combined with anomaly detection using Edge AI, minimizes latency and enables rapid response. To address privacy concerns, Federated Learning (FL) is incorporated to enable decentralized model training without transferring raw patient data. A hybrid anomaly detection model based on time-series behavioral analysis identifies patterns of early cognitive decline. Simulation-based evaluation suggests that the proposed framework improves detection accuracy and reduces latency by up to 40-50% compared to traditional cloud-based systems. This architecture provides a scalable and privacy-aware solution for intelligent healthcare systems. In addition, such intelligent monitoring systems can support healthcare professionals in making timely and informed clinical decisions. The integration of advanced data analytics with real-time monitoring provides a promising direction for improving early diagnosis and long-term patient management in neurodegenerative diseases.

Keywords: Alzheimer's disease, Internet of Things, remote patient monitoring, edge AI, smart healthcare, data privacy

1. Introduction

This framework has arisen from digital phenotyping and will align with the expected culture shift of 2025-2026. Digital Phenotyping will provide continual sources of data on biological evidence, collected or integrated, and, over time, will continue to monitor possible changes in neurodegeneration. Continuous integration of this type of data will alleviate the problems associated with traditional methods of capturing data in episodic events. Evidence from recent longitudinal studies suggests that passive multi-modal sensors (e.g., gait patterns, typing behavior, and circadian rhythm) can improve the sensitivity of detecting early cognitive decline. The above rationale supports the development of digital biomarkers for the early detection of neurodegenerative diseases based on the identification of minor functional changes. Minor functional changes may include, but are not limited to, uncharacteristic gait patterns and/or reduced velocity of walking and/or increased fragmentation of sleep. These minor functional changes often occur prior to the observation of a significant buildup of amyloid beta and tau proteins, which are primarily measured by positron emission tomography (PET) scans or the collection of cerebrospinal fluid via a lumbar puncture

(LP). Therefore, with the adoption of a system for the continuous and non-invasive monitoring of patients, more comprehensive assessments of behavioral and psychological symptoms of dementia (BPSD) may occur and allow for earlier initiation of treatment and/or therapy in addition to providing a comprehensive assessment of BPSD in the natural living environment. This approach paves the way for developing management programs that can be scaled worldwide to address the needs of rapidly aging populations. Alzheimer's disease (AD) is one of the most prevalent neurodegenerative disorders, impacting millions worldwide. The designation "AD" reflects progressive neurological deterioration characterized by impairments in cognitive function and memory [1], [2]. With the global increase in the elderly population, the number of individuals affected by AD is expected to grow, posing significant challenges to healthcare systems. One of the main challenges in managing Alzheimer's disease is early diagnosis. This is challenging because early symptoms are often subtle using traditional methods. Regular medical checkups are the usual approach; however, they do not adequately capture behavioral changes, so the diagnosis often happens quite late. Thanks to advances in IoT, modern healthcare services have developed remote patient monitoring solutions. Patients can be continuously monitored using sensors that record their activities, physiological signs, and interactions with the surrounding environment. Furthermore, the increasing availability of wearable technologies and smart sensing devices has accelerated the adoption of digital health solutions. These technologies enable continuous tracking of patient activities in real-life environments, which provides more reliable and context-aware data compared to traditional clinical assessments. As a result, digital phenotyping has emerged as a powerful tool for understanding subtle behavioral changes associated with neurodegenerative diseases. Still, current IoT-based health monitoring systems are limited in terms of excessive use of cloud infrastructure, higher data processing latency, higher risks of data leakage, and low ability to identify patterns characteristic of early stages of Alzheimer's disease. To solve the mentioned challenges, a secure and smart IoT-based solution based on Edge Artificial Intelligence and federated learning is proposed in this paper. In addition, intelligent monitoring frameworks can assist clinicians in making data-driven decisions by providing continuous insights into patient behavior. Such systems are particularly valuable in managing chronic neurodegenerative conditions, where early intervention plays a critical role in improving patient outcomes.

2. Background and Motivation

2.1 Alzheimer's Disease and Early Detection

It can take years for Alzheimer's to develop, and stages range from minimal impairment to terminal dementia. Early detection is challenging because symptoms are often subtle. Current research has shifted from invasive biomarkers (like PET scans) toward non-invasive digital biomarkers. In recent years, significant attention has been given to early-stage diagnosis, as interventions at this stage can potentially slow disease progression and improve quality of life. Therefore, identifying reliable early indicators remains a major research focus. Early detection not only improves treatment outcomes but also reduces the overall burden on healthcare systems by enabling timely interventions.

2.2 IoT in Healthcare Systems

IoT has revolutionized healthcare through continuous patient monitoring and real-time data collection. In Alzheimer's applications, IoT devices monitor behavior over extended periods to provide insights into disease progression [3]. These technologies also contribute to reducing hospital visits and improving patient comfort by enabling remote and continuous health monitoring.

2.3 Edge AI and Federated Learning

Edge AI enables device-level data processing, reducing latency and allowing for faster decision-making. Federated Learning enhances privacy by keeping sensitive patient data on local devices and sharing only model updates [4], [5]. The integration of these technologies provides a balance between computational efficiency and data privacy, which is essential in sensitive healthcare applications. This combination enables scalable and secure deployment of intelligent monitoring systems.

3. Related Work

Recent advancements also highlight the role of privacy-preserving federated learning and real-time edge intelligence in improving healthcare monitoring systems [5],[6]. Edge computing was developed to process data closer to the source to improve efficiency. Federated Learning has gained interest for its privacy protections in distributed environments [8]. Few papers have focused specifically on the identification of Alzheimer's disease. While many existing solutions rely heavily on centralized cloud infrastructures, they often face limitations related to latency and data privacy. Emerging decentralized approaches aim to address these challenges by distributing computation closer to the data source. Additionally, recent research has emphasized the importance of combining multiple technologies, such as IoT, Edge AI, and Federated Learning, to create more efficient and secure healthcare systems. However, challenges remain in achieving optimal system performance while maintaining privacy and scalability.

4. Proposed Framework

The framework consists of a multi-layer architecture:

Sensor Layer: Includes wearable devices (smartwatches and health trackers) and ambient sensors (motion sensors and environmental monitors) to collect physiological data (heart rate and activity levels) and behavioral data (movement patterns and sleep cycles).

Edge AI Layer: Edge nodes perform data preprocessing, feature extraction, and real-time anomaly detection to reduce cloud dependency.

Federated Learning Layer: Enables collaborative model training across multiple devices without sharing raw data, reducing data breach risks [9].

Cloud Layer: Responsible for aggregating global models, long-term analytics, and clinical decision-making support.

Security Layer: Ensures protection through end-to-end encryption, authentication mechanisms, and access control policies [10].

This layered architecture ensures modularity, allowing each component to be independently optimized and updated without affecting the overall system performance. Such flexibility is essential for adapting to evolving healthcare requirements.

5. Methodology

5.1. Data Processing and Feature Extraction

Collected data is processed via time-series analysis to extract irregularities in movement, sleep duration, and activity frequency. In addition, data preprocessing techniques such as noise filtering, normalization, and missing value handling are applied to ensure data quality and consistency. Feature extraction focuses on identifying meaningful temporal patterns, including variations in daily activity cycles, sleep fragmentation, and changes in mobility behavior. These features are then used to construct individualized behavioral profiles, which serve as a baseline for detecting deviations associated with early cognitive decline. Furthermore, statistical and signal-processing methods are employed to enhance feature representation and improve the robustness of the analytical model.

5.2. Behavioral Modeling and Anomaly Detection

A hybrid AI model identifies deviations from a patient's unique behavioral baseline to detect early indicators of cognitive decline. The use of personalized behavioral baselines allows the system to adapt to individual differences among patients, thereby improving detection accuracy and reducing false positives.

5.3. Federated Learning Workflow

The workflow involves:

(1) training local models on edge devices

(2) transmitting model updates

(3) cloud aggregation

(4) global model redistribution

The proposed approach is designed to be adaptable to different patient profiles, allowing the system to continuously refine its detection capability based on evolving behavioral patterns.

6. Experimental Evaluation

The system was assessed using a synthetic dataset representing patient behavior. Simulation results demonstrated a 40-50% reduction in latency and improved detection accuracy and privacy compared to conventional cloud systems. The simulation environment was configured to reflect realistic variations in patient behavior, allowing for a more comprehensive assessment of system performance under different conditions. In addition, multiple simulation scenarios were considered to evaluate system robustness under varying conditions, ensuring that the proposed framework maintains consistent performance across different data patterns.

7. Discussion

An effective remedy for intelligent healthcare systems is provided by the integration of Federated Learning and Edge AI.

Key Advantages	**Challenges**
Real-time monitoring	Sensor reliability
Privacy preservation	User adoption
Scalability	Lack of standardization

Despite these advantages, further validation using real-world clinical datasets is necessary to fully assess the effectiveness of the proposed system. Moreover, the integration of secure and scalable technologies can significantly enhance the reliability of remote patient monitoring systems in real-world applications.

8. Conclusion and Future Work

This article introduces a secure and intelligent RPM framework that is based on the Internet of Things (IoT) for the early detection of Alzheimer's disease [11]. The integration of Federated Learning and Edge AI enables real-time monitoring, reducing latency and safeguarding privacy. The proposed system is a substantial advancement in the development of intelligent healthcare solutions for the future. Potential areas for future research include:

- Integration with blockchain
- Explainable AI models
- Validation of clinical findings using actual patient data

Future developments in intelligent healthcare technologies are expected to further enhance the capabilities of such monitoring systems, contributing to more personalized and efficient patient care. Overall, the proposed framework highlights the potential of combining advanced computational techniques with healthcare monitoring systems to address current limitations in early disease detection.

Author Contributions

Both authors participated in writing the manuscript, critically revised it for important intellectual content, and approved the final version for publication.

Conflict of Interest

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Evaluation of Factors Affecting the Activity of University Students as Specialists in Modern Research

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Abstract: A student with basic knowledge (who receives this knowledge directly from traditional education) is often not satisfied with the knowledge in the specialty he/she has acquired during the educational process. He/she prepares himself/herself as a future specialist through other possible means. Using the opportunities provided by society, the student improves and develops throughout the academic years. At the same time, one of the main problems is assessing the knowledge acquired by the student in traditional education and in extracurricular activities. The article provides a comparative analysis of the models applied in various studies to assess the knowledge and skills of the student during his/her studies at the university. As a result of the analysis, it became clear that researchers mainly study the behavior and success of the student, his/her extracurricular knowledge and skills, individually for each academic year. In the studies, the skills arising from basic knowledge, the student's personal interests, social activities, language skills, etc., are examined, and the data collected through various surveys are systematized, and various models are proposed, taking into account cause-and-effect relationships. The models proposed in the studies allow predicting the direction in which the student is formed as a specialist. On the other hand, using the results, it is possible to direct the student more correctly, taking into account his personal abilities.

Keywords: Assessment of students, educational performance, individual characteristics, personal interests, language skills, fuzzy model

1. Introduction

Modern information technologies allow solving problems that arise during the acquisition of knowledge, regardless of where it is stored or financial, administrative, or other constraints. The global network can deliver large volumes of information resources digitally to any user. The ability to access information from various sources allows you to answer any query and find related information. Since they do not require special knowledge from users (in terms of technical or software knowledge), these resources are accessible to every user. In such a situation, the task of adapting the modern educational process to this situation is also faced. These resources are accessible to every user because they do not require special knowledge (both technical and software). In such a situation, the task of adapting the modern educational process to this situation is also faced. In this case, each student in the education system becomes the subject of his own development, is constantly in search, and does not limit himself to the knowledge provided by standard education. Naturally, the student wants to adapt to the requirements of the labor market, and to realize himself as a specialist in the future, he also tries to establish active relations with the environment. Only in this case can the student express himself and develop to the fullest.

Thus, each student, who has basic knowledge, improves and develops as a "student" of the university throughout the entire educational process, using not only the knowledge provided in traditional lectures, seminars, and laboratory subjects but also various sources the internet, knowledge provided in various educational courses, and information obtained by participating in quizzes, subject Olympiads, symposiums, and conferences [1]. In this case, one of the main problems is to determine the extent to which the knowledge acquired by the student affects his or her development as a future specialist [2].

2. Analysis of Existing Studies

A fuzzy model is proposed to assess the impact of students' extracurricular activities on their academic performance using a Bayesian approach [3]. It is noted that the model can consider various types of extracurricular activities that a student engages in in addition to their major.

A model is proposed for how information provided in standard education is stored in a student's memory and used during academic attestation, depending on the student's psychophysiological characteristics [4]. The study refers to the student's sociability, emotional stability, preference, responsibility, etc., characteristics. The influence of individual characteristics on the results of attestation was studied through a sociological survey [5].

A review of Blackboard, Desire2Learn, Moodle, WebCT, Sakai, Virtools, WorldToolKit, Juggler, Dolphin, ToolBook, Act3D, Amira, Unity3D, Alternativa3D, and other systems widely used in modern education showed that, as a rule, a modern educational system is actually a collection of static hypertext documents. All students receive the same educational material and similar tasks to manage the acquired knowledge and skills, regardless of their individual characteristics [7]. On the other hand, the collective activities of students during the attestation stage require a different approach to the mechanism of their knowledge acquisition [8].

The current era, characterized by rapid technological changes and the application of artificial intelligence in most infrastructure and production areas, places high demands on the quality of training specialists for the formation and development of the information society. One of the main requirements for university graduates is that they must possess a number of professional and psychological characteristics that can provide them with a high rating in the competitive labor market.

Naturally, when choosing a future professional direction, a student should evaluate not only his desires and aspirations but also his opportunities arising from his personal qualities [9]. In some cases, these assessments are incomplete because they are subjective, in which case the student seeks to meet these requirements by changing the direction of their extracurricular activities [10], [11]. Of course, to give the future specialist the right direction by taking into account individual characteristics, we must have a model that evaluates these characteristics [12]. Researchers use various methods to model the role of individual characteristics in the formation of a future specialist, including quantitative assessments of competencies with a systematic approach [12], based on various social surveys, such as the 16-factor Kettell survey [13], or psychological tests [14]. It should be noted that the main idea in modeling the impact of individual characteristics on specialist training is that these characteristics are not uniform and depend on subjective assessments. It is under these conditions that various researchers prefer fuzzy models[15], [16], [17]. The fuzzy approach has shortcomings, particularly that it can model individual characteristics not assessable with quantitative measures through membership functions, making this methodology necessary.

3. Comparative Analysis

Activities related to quality control of specialist training at the university should cover all areas of the educational process, as well as quality control of the resources that provide this activity [1]. In some cases, assessments of the quality control of specialist training are subjective in nature because they are influenced by various objective and subjective problems and difficulties. One of the most important of these problems is the problem of monitoring and evaluating the development of students' general cultural and professional competencies. In the training process, researchers face serious difficulties due to uncertainty in determining the nature and structure of competencies, as well as the methods and tools for their monitoring and assessment. According to sociological studies, most researchers identify the lack of reliable and convenient assessment methods as a significant problem [18]. However, it should be noted that many researchers prefer traditional assessment of knowledge, since the factors in the process of assessing specialist training are probabilistic and sometimes uncertain. This assessment occurs at all stages of education: ongoing assessment in seminar and laboratory classes, midterm assessment of students, and final assessment of graduates. As a result, although the higher education system is said to be focused on developing skills in students, in reality, a situation arises where traditional knowledge is valued.

Researchers prefer to use risk analysis in assessments [19]. It is known that in risk theory, the probability of making incorrect or unnecessary management decisions arising from the characteristics of certain events and types of human activity, or the probability of obtaining unplanned results when carrying out a certain activity, is considered risk [20], [21], [22].

The research study analyzes the methodological foundations of a “serious games”-based measurement mechanism for assessing the professional skills of university students [23]. The study was carried out through observable behavioral indicators within game scenarios for competency indicators (problem solving, decision-making, collaboration, and systematic thinking). The assessment process was based on quantitative measurements and statistical analyses, and compared with traditional survey and test methods. The results indicate that the serious games approach increases the reliability and discriminability of the measurement and reduces the risks of subjective assessment. This methodological framework acts as an alternative model that can be applied to multidimensional and dynamic assessments of professional levels in higher education. Another research study was conducted to examine the structural and methodological foundations of a pedagogical assessment model aimed at diagnosing the professional and cultural competencies of higher education students [24]. The authors have developed a multidimensional assessment framework for cognitive, behavioral, and value-oriented components by dividing competencies into a system of measurable indicators. The diagnostic process is based on a combination of tests, observation protocols, and expert assessment methods to collect empirical data. The collected data is analyzed through statistical processing, allowing for differentiation of competency levels. The article makes a scientific contribution to the field of professional-level assessment in higher education by presenting a systematic methodological approach that increases the reliability of pedagogical diagnostics and the objectivity of measurement. The main goal of universities' activities at all levels of modern higher education, undergraduate, graduate, and postgraduate, is to prepare qualified specialists who are ready for professional activity and development, have social and professional mobility, and can adapt to changing external conditions [25], [26], [27].

As is known, the state standards for specialty modules include competencies that characterize the specificity of the educational process and the quality of training for modern university graduates. The structural elements of competence are a generalized expression of experience consisting of the integration of activities arising from the individual characteristics of the student, teaching methods, and techniques for solving problems that may occur in teaching into a single unit. The main requirement for competencies includes the constant updating and enhancement of knowledge and the acquisition of new information by university students to successfully solve tasks. The university raises the issue of the continuity of competence development at all stages of training, from the first stages of higher education to the final years, and requires the consideration of specific competences in each direction of training [28].

Educational institutions around the world provide guidance and counseling services to help students effectively overcome life's challenges and obstacles. Researchers have extensively analyzed the factors that may influence students' academic performance[30], [31]. Previous studies have used correlation analysis, decision trees, and random forests to identify factors affecting student performance [32].

Fuzzy sets have been used to characterize students' knowledge status, which has highlighted the lack of collaborative support and feedback in e-learning systems [33]. Similarly, other researchers have compared recommender system methods with traditional regression methods and applied them to educational data for intelligent tutoring systems, increasing the accuracy of predicting student performance [34]. The authors discussed building a semantic student profile using fuzzy logic and online survey results that only use knowledge about students' interests and style to predict students' learning preferences based on their interests and learning style[35]. Later, some authors emphasized the application of fuzzy sets to data representation, claiming that self-awareness is essential to their model [5], [17]. Several studies have proposed systems that identify different stages of truancy and offer motivational phrases and advice to support students in different scenarios[2]. A system based on comprehensive information about students' grades in various subjects provides results that increase the efficiency and accountability of decision-making and improve the educational system at the university[36]. An intelligent system for determining student progress has been developed using various methodologies such as the Big Five Factor and Five Factor Model, intelligence quotient tests, and self-assessment [37]. The contributions of this work include data set collection; comparative analysis, which machine learning algorithm is better at predicting openness to new opportunities and career readiness; and providing empirical evidence of the interaction between career aspects of students' personalities and their impact on transition readiness.

4. Conclusion

The models proposed in the analyzed research studies are built for a specific case, taking into account the profile of each university and the profile of the specialty. Naturally, these models cannot be applied to other universities without the same changes**.** This is primarily due to the fact that the parameters used in building the proposed models are of different natures: deterministic, probabilistic, and fuzzy. On the other hand, each university is independent in terms of both its internal structure and educational activities, which individualizes the educational process. Currently, in most universities, the average grade of academic performance is taken as an indicator of a student's success, while in others, the student's behavior and social activities also affect successful completion of the university. On the other hand, the availability of social and technical infrastructure at universities (library, cafeteria, dormitory, cultural events, etc.) directly and indirectly affects students' academic success. It is known that a student choosing a professional career should evaluate not only their dreams and aspirations but also their capabilities arising from their personal qualities. Researchers use various methods to model the role of individual characteristics in the formation of a future specialist. These methods include quantitative assessments of competencies using a systematic approach based on various social surveys, such as the 16-factor Kettell survey or psychological tests, as well as fuzzy models, correlation analysis, decision trees, and random sampling methods. Studies have shown that while the main factor in assessing a student's level of preparation is their academic performance, universities also require students to demonstrate cultural competencies. The main reason for this is that the structural elements of competence are a generalized expression of experience consisting of the integration of activities arising from the individual characteristics of the student, teaching methods, and techniques for solving problems that may occur in teaching into a single unit. The university raises the issue of the continuity of competence development at all stages of training, from the first stages of higher education to the last courses, and requires the consideration of specific competences in each direction of training.

Author Contributions

All authors participated in writing the manuscript, critically revised it for important intellectual content, and approved the final version for publication.

Conflict of Interest

The authors declare no conflicts of interest.

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Software Tools for the Implementation of Solutions to Management Problems based on Fuzzy Logic

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Abstract: As artificial intelligence primarily processes incoming data, its scope is limited. Therefore, the interaction of artificial intelligence and humans is used to expand the scope of application. Such a partnership allows for solving complex problems and obtaining accurate results. Such problems are currently solved thanks to the experience and intuition of prominent specialists. However, in technical fields, there is a risk of making a serious mistake if the initial conditions and assumptions are not carefully studied. For example, unexpected failures in security systems, unreasonable results in information systems, unbalanced automation systems, and so on all arise because project conditions differ significantly from real conditions. For technical purposes, fuzzy logic is considered in a broad sense. Fuzzy set theory allows solving complex technical problems, such as technical diagnostic problems. Thus, fuzzy relationships allow the establishment of approximate relationships between causes and effects based on expert assessments. Expert assessments of the current technical condition of electrical equipment, carried out on the basis of fuzzy causal relationships of symptoms and defects, can increase the reliability of determining the causes of defects.

Keywords: Artificial intelligence, diagnostic systems, deterministic knowledge, fuzzy set, adaptive fuzzy model

1. Introduction

The generalization of expert assessments allows for increasing the reliability of the diagnosis of the technical condition of the facilities of the power grid complex. Modern diagnostic systems, which are necessary to analyze the symptoms of faults in the electrical network, must be based on current or expert information about the location and causes of faults, while monitoring the current technical condition and the deviation limits of certain technical characteristics. Recently, various new effective approaches have been developed based on artificial intelligence methods, namely expert systems, fuzzy logic, image recognition through artificial neural networks, and fuzzy relationships [1].

2. Application of Diagnostic Systems

The field of application of diagnostic systems includes monitoring the operation of electrical devices of the power grid complex, monitoring trends and monitoring instruments in complex automated production, and controlling the quality of electrical energy. The choice of the most appropriate strategy for diagnostic examination is determined by knowledge of the specific characteristics of the process to be monitored. The most effective solution for assessing the current technical situation can be considered artificial intelligence methods. If deterministic knowledge is not sufficient or mathematical modeling requires a high cost or does not have sufficient accuracy, it is advisable to use methods based on modeling the operator's knowledge. This can be done using logical inference strategies such as expert systems, fuzzy logic output systems, or artificial neural networks. This allows determining the technical condition of the facility based on fuzzy, inaccurate, and incomplete knowledge. Currently, systems for diagnosing and monitoring the technical condition of high-voltage electrical equipment are expert automated systems in "advisory" mode. There are two directions for solving the following problems: determining the technical condition of electrical equipment in order to detect defects and malfunctions; selecting optimal control effects on electrical equipment of the power grid complex in order to increase the reliability of the facility's operation and extend its service life.

Thus, information about the normal and abnormal operation of the process can be used to detect malfunctions. As a result of the application of fuzzy logic methods, knowledge about the process, which exists in the form of observations and verbal descriptions, can be used in the classification of processes. For this purpose, linguistic variables are used, expressed as weighting coefficients for values between "true" and "false". This is achieved by introducing the concept of a “membership function”. Membership functions should accurately describe the state of the system being diagnosed.
Thus, it is shown that fuzzy set theory and fuzzy logic represent a promising scientific direction in technical diagnostics, allowing experts to create a formalized fuzzy mathematical model of cause-and-effect relationships by formulating their knowledge in the form of verbal assessments and linguistic variables [2], [3].

3. Fuzzy Logic Packages

Currently, the global market for commercial software products for working with fuzzy logic is actively developing. It provides over 100 software packages that use fuzzy logic to one degree or another. Several software companies are leaders in this field. Their tools are aimed at applying fuzzy logic to as many areas and applications as possible. These include the CubiCalc package from Hyper Logic, FuzzyTECH (Inform Software), FIDE (Ap-tronix), extension packages for MATLAB: Fuzzy Logic Toolbox (included with MATLAB) and FlexTool for MATLAB from Cynap Sys, as well as the JFS package (developed by Jan Mortensen), and others. Most of the software packages listed have a full-featured user interface and advanced data import/export tools.

Fuzzy logic packages can be divided into the following groups according to their capabilities.

1. A program that generates code for microcontrollers that run on fuzzy algorithms. Typically, the code is generated in basic assembly language.
2. Packages that allow you to create expert systems based on fuzzy logic. In other words, fuzzy rules and membership functions are defined by subject matter experts. All packages allow the researcher to choose the type of membership functions (triangular, trapezoidal, Gaussian, etc.), the fuzzy output mechanism (Mamdani, Sugeno, Tsukamoto, Larsen), and the compilation and clarification method. Working with the package is facilitated by graphical representations of fuzzy models, response surfaces, and mnemonics of other dependencies.
3. Packages that allow you to build dependency approximators and classification systems based on adaptive fuzzy inference models.

The first group includes FuzzyTECH and FIDE tools. Software packages from the last two groups are of primary interest when modeling complex systems.

Most of the software listed above allows you to create fuzzy expert systems. The price of some programs can reach several thousand dollars in standard delivery. And only a few of them allow you to adaptively configure the structure and parameters of the fuzzy model.

Thus, during the analysis, no programs focused solely on working with adaptive fuzzy systems were identified. Among the packages reviewed, FuzzyTECH and the Fuzzy Logic Toolbox for MATLAB Extension have the most versatility [4]. Let us focus only on the features of the adaptive configuration capabilities of the fuzzy knowledge base in these packages [5], [6].

FuzzyTECH implements some methods for structural adaptation of a fuzzy model or methods for generating fuzzy “If-Then” rules. One of them is that first, a complete base of fuzzy rules is formed, and each of them is initially given a random importance coefficient. Then, one of four learning methods is selected (RealMethod, RandomMethod, Batch_Learn, Batch_Random), during which time the importance coefficients are refined. If the significance coefficient is close to zero, it is suggested that the rule be deleted, but the final choice remains with the researcher.

It should be noted that assigning importance coefficients to rules contradicts the ideology of fuzzy systems, which assumes that all rules have equal weight. This approach is closer to hybrid neuro-fuzzy systems, where the weight coefficients of neurons play the role of the importance coefficients of fuzzy rules.

The second method available in FuzzyTECH uses a genetic algorithm to optimize the number of terms for each system variable using general forms of membership functions and a symmetric fuzzy partition [3]. The disadvantage of this method is the large size of the problem, which increases exponentially with the number of system variables. Furthermore, the problem of optimizing the number of terms is less significant than the problem of generating a set of rules from experimental data.

The Fuzzy Logic Toolbox for MATLAB has more advanced capabilities than FuzzyTECH for estimating nonlinear dependencies with adaptive fuzzy models [7]. A necessary advantage is that the MATLAB mathematical environment is popular in the CIS, and there is sufficient documentation and information sources on its use. The main functions and algorithms in the Fuzzy Logic Toolbox extension are implemented for the Sugeno inference engine (TSK). It is possible to work with both descriptive and approximate rules in the TSK form.

The development of a fuzzy model is carried out in two stages. In the first stage, the creation of rules and finding the boundaries of terms is carried out based on the subtractive clustering method. The second stage uses AN-FIS (Adaptive Network-based Fuzzy Inference System) technology [8], an iterative procedure for constructing membership functions using the backpropagation method. This package does not provide training for Mamdani models.

Using the additional Optimization Toolbox package, it is possible to implement adaptive adjustment of Mamdani membership functions, but the fuzzy rules must be defined independently. There is also no possibility to use evolutionary computations and genetic algorithms in the methods of tuning adaptive fuzzy models in the fuzzy logic toolbox. This feature is available in another MATLAB extension package, CynapSys's FlexTool package. This is the only widely recognized commercial package that offers full genetic tuning of all parts of a fuzzy model [9].

An adaptive fuzzy model has the ability to adapt to a specific fuzzification method, so the criterion for choosing one or another method should be its lowest computational complexity. To train a model on experimental data, you can choose from three types of genetic algorithms - standard GA, micro-GA, and steady state GA.

The last two are modifications of the standard GA and are described in detail in [4].

The disadvantages of the FlexTool package include:

1. The high price to which you need to add the price of the MATLAB environment, then the total cost of the package will be 2.5-4.5 thousand dollars, depending on the delivery option.
2. Lack of documentation in Russian for the FlexTool package.
3. The methods used in the FlexTool package for training a fuzzy model using a genetic algorithm are not described in the system reference book.

A review of well-known software packages for fuzzy modeling demonstrated that most of them are focused on building fuzzy expert systems; only one package uses genetic algorithms to create a fuzzy model, when the parameters of the member functions and rules are set by the expert [10], [11].

4. Conclusion

1. The features of the manifestation of information uncertainty in the course of natural and technological processes and the methodological means of studying the issues of managing these processes in such conditions are explained [12].

It has been determined that four levels of uncertainty are distinguished:
- low level that does not affect the main stages of the process of preparing and implementing a management decision.
- medium level, requiring reconsideration of some stages of development and implementation of the decision.
- high level, involving the development of new procedures.
- an ultra-high level that does not allow for the assessment and adequate interpretation of information related to the emerging situation.

  Ultra-high levels of uncertainty lead to ineffective decisions because poorly structured, difficult-to-understand, and unreliable information make it difficult to make effective decisions. Taking into account uncertainty levels allows for their use to be presented analytically [13], [14].

When a technologist or dispatcher encounters uncertainty in the decision-making process, they act in different ways:

- Often, one ignores the existence of conscious (or unconscious) uncertainty and uses deterministic models.
- Selects the type of uncertainty from the perspective of most importance and uses the appropriate theory. Currently developed decision-making methods only help to choose the best of many possible decisions under a certain level of uncertainty.
- It conducts more systems research or obtains information through supervision (adaptation and training) or management.

In management theory, several main types of uncertainties are distinguished: parametric uncertainty, non-parametric uncertainty, undecidable uncertainty, nonlinear uncertainty, uncertainty of external conditions, and uncertainty of the goal.

When solving some practical problems, it is necessary to eliminate the uncertainty in the initial data or to take into account the presence of uncertainty in this data. In such cases, the rigorous mathematical formulation of practical problems creates the need to use models that take into account the uncertain nature of the information, since in real situations, complete information about the conditions for solving the problem is rarely available. Solving such problems is currently considered one of the issues of significant theoretical and practical importance. The application of various research methods and computational tools allows obtaining solutions that take into account the uncertainty of the initial data and make judgments about the processes under study that have real characteristics [15].

To perform the fuzzy logic-based research process, the Fuzzy Logic Toolbox package is used in the MATLAB environment. In interactive mode, the user can solve various difficult problems by using the capabilities of the package to perform fuzzy logic-based research. This software environment also allows for the development of a neuro-fuzzy model and the generation of appropriate results.

2. Controlling gas transportation processes is considered one of the most pressing technological problems. A reliable solution to these problems is determined, first of all, by the precise identification of the factors influencing these processes and the level of their consideration in the relevant behavioral models. In this regard, a methodology is proposed for estimating hydraulic pressure losses during gas movement in a gas pipeline, within the framework of uncertain knowledge of the values of the pipeline operating parameters (hydraulic friction coefficient and pipeline diameter), depending on the flow characteristics and the influence of influencing factors. The proposed methodology can be used to assess hydraulic pressure losses

that may arise during gas transportation through main pipelines due to the influence of various factors, using uncertain information about changes in the gas flow regime, as well as the diameter of the pipeline, so that the assessment results obtained in this way can allow for the necessary efficiency in taking measures to regulate the technological regime of compressor stations.

3. Taking into account the uncertainty of information, a volumetric method of estimating gas field reserves has been introduced. With the presented method, it is possible to calculate the gas volume based on the fuzzy known values of the calculation parameters included in the formula: gasification, porosity, layer thickness, and gasification area.

Author Contributions

Nurlan Karimli conducted the literature search and drafted the manuscript. Assoc. Prof. Rana Hajiyeva. supervised the study, provided critical guidance on content and structure, and reviewed the manuscript.

Conflict of Interest

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Remote Patient Monitoring Based on IoT Technologies

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Abstract: The rapid advancement of Internet of Things (IoT) technology is revolutionizing traditional healthcare infrastructure, offering innovative solutions, especially in the field of Remote Patient Monitoring (RPM). This article extensively discusses the entire lifecycle of IoT-based RPM systems, including their fundamental principles and architecture, applications, associated technology, challenges, and future scope. According to various studies, not only does this help in the betterment of patient health, but it is also economically viable to the system, helping in the reduction of hospital and overall healthcare expenses. In this article, the importance of RPM in the treatment and monitoring of chronic diseases, its applications in the care and monitoring of elderly patients, and in cardiology and post-operative care have been discussed in detail. But for the widespread adoption of IoT-based RPM, various factors need to be considered, including data security, regulatory issues, and technological synergies. In addition, the importance and future scope of various techniques and technologies, including TinyML, Federated Learning, and Blockchain, have been discussed.

Keywords: remote patient monitoring, IoT, AI, edge computing, federated learning, TinyML, data security, healthcare informatics, wearable technologies, telemedicine

1. Introduction

With an aging global population and the rise of chronic illnesses, the current healthcare system is under growing pressure to deliver sustainable and effective care services. Cardiovascular disease, diabetes, and chronic obstructive pulmonary disease are among the conditions that contribute substantially to the global burden of disease. The conventional and reactive medical approach may encounter difficulties such as delayed diagnosis and high costs. To collaborate with this issue, the current healthcare system requires a revolutionary approach that can extend healthcare services beyond the hospital walls [1].

RPM refers to the capability to continuously collect, transmit, analyze, and interpret patients' physiological information (such as heart rate, blood pressure, and glucose levels) in their homes or during their daily activities through IoT devices. It signifies a paradigm shift from reactive to proactive and sophisticated medical practice. Research has demonstrated that RPM initiatives can decrease hospital readmissions by up to 50% for patients with conditions such as heart failure and chronic obstructive pulmonary disease (COPD).

The objective of this article is to present a detailed analysis of the IoT-based RPM ecosystem. We will discuss its technology architecture, overall benefits, various application areas, challenges it currently faces, and future trends of IoT-based RPM systems. In addition to this, examples and statistics will be used to show the actual impact of these systems.

2. Technical Architecture of IoT-Based RPM Systems

IoT-based RPM systems possess a sophisticated yet well-organized modular technology architecture with various layers involved. Each of these components will be discussed in detail below:

2.1. Sensory Rugged and Wearable Devices

- It is the first point of contact between the physical world and digital information. Modern RPM sensors have evolved from simple temperature monitors to more complex, multi-parameter devices. Examples include:
- Electrocardiogram (ECG / EKG) patches: Devices that can be brought in externally and record the heart rhythm continuously for a week or more (e.g., Zio® patch).
- Wearable glucose monitors (CGM): Sensors (e.g., Dexcom G6, FreeStyle Libre) that measure glucose levels in the fluid under the skin and transmit the data to a smartphone [2].
- Smart watches and fitness trackers: Many commercial products, such as the Apple Watch (which can detect atrial fibrillation) [3]. Fitbit and Garmin devices are integrated into personal health monitoring.
- Smart blood pressure cuffs and pulse oximeters: Bluetooth-enabled devices that sync data directly to cloud platforms.

These devices are controlled by low-power microcontrollers (e.g., ARM Cortex-M series) optimized for energy efficiency and use communication protocols such as Bluetooth Low Energy (BLE), Wi-Fi, Zigbee, or Insect Network (LoRaWAN).

2.2. Network and Edge/Fog Computing Layers

The data stream collected from the sensors is transmitted to the processing through the network layer. Here, an important concept that departs from the traditional "sensor-cloud" model is Edge and Fog Computing [4].

1. Edge Computing: Pre-processing data at the point of origin (for example, on the patient's smartphone or a special gateway device). This is used to filter out noisy data, detect anomalies (such as a sudden increase in heart rate) for basic alerting, and transfer only meaningful data or aggregated statistics to the cloud. This can reduce network throughput by up to 60% and minimize latency [5].
2. Fog Computing: It is an intermediate layer between the Edge and the cloud, such as a hospital network using local servers. It provides more computing power for more complex analytics or aggregation of information across multiple patients.

2.3. Cloud Platform and Data Analytics

The cloud is the "brain" of the RPM system. It is a scalable storage and computing resource. Here, the data is cleaned, structured, and prepared for analysis. Artificial Intelligence (AI) and Machine Learning (ML) are critical at this point [6].

Predictive Models: These algorithms can predict future events related to health, like hypertensive crisis or hypoglycemia.

Anomaly Detection: This automatically identifies behaviors that are not within the patient’s normal baseline.

Personalized Recommendations: These may provide lifestyle recommendations or changes to medication dosages based on the patient’s condition.

Doctors and nurses use this cloud-based platform to access patient information, trends, and alerts generated by the AI system via a web interface or mobile application.

2.4. User Interface (UI) and Notification System

The final element of an effective RPM system is a clear, action-oriented interface. It is intended for both the medical staff and the patient. For medical staff, dashboards display a list of patients, their risk levels (e.g., color-coded), and alerts that require immediate intervention. Apps for patients show their own information, progress, and personalized recommendations. The alert system notifies both the patient and their doctor immediately of critical situations via email, SMS, or app notifications.

3. Advantages and Effects of RPM

Implementing an IoT-based RPM leads to multiple benefits for all stakeholders – patients, healthcare providers, and insurers.

3.1. Benefits for Patients

Improved Quality of Life and Comfort: Patients can often stay in the comfort of their own homes, avoiding the stress and anxiety of going to the hospital. This is especially beneficial for patients with weakened immune systems or limited mobility.

Enhanced Patient Education and Self-Care: The ability to view their own real-time data makes patients more involved in managing their own health, encouraging them to make healthier lifestyle choices [7].
Earlier Intervention and Better Outcomes: Continuous monitoring detects potential problems long before symptoms appear, meaning treatment can be quicker and more effective.

3.2. Benefits for Health Care Providers

Decision Support and Proactive Care: RPM provides physicians with objective, quantitative data to inform their clinical decisions. Instead of relying on the complaints of the patients, they can act on the basis of trends that have been supported by data.

Efficient Allocation of Labor and Resources: RPM helps in the efficient allocation of medical staff's time and resources to those patients who require it. Research has proven that with the help of RPM, 4-5 times more patients can be managed by the nursing staff compared to conventional practices [8].
Increasing Revenue Streams: In the US, as well as other countries, insurance companies, like Medicare's payment codes for "Remote Monitoring of Chronic Disease Patients," pay for RPM services, thus providing a new revenue stream to medical providers.

3.3. Benefits for Healthcare Systems

Reduced Hospital Readmissions and Costs: Better management and early intervention dramatically reduce the number of short-term hospital admissions and readmissions. For example, RPM programs for heart failure have been shown to reduce rehospitalization rates by 30-50% [9]. Improved Patient Satisfaction: A comfortable, proactive, and personalized care experience significantly improves overall patient satisfaction.

3.4. Application Areas and Real World Examples

The application of RPM is widespread among different clinical specialties and disease categories:

Chronic Disease Management Diabetes: Continuous Glucose Monitors (CGMs) provide real-time glucose readings, pinpoint insulin doses, and help prevent dangerous hyper- and hypoglycemia. Studies show that patients using CGM experience significant reductions in HbA1c levels [2].

Hypertension and Cardiovascular Diseases: Home blood pressure monitors share data directly with the doctor, allowing to assess the effectiveness of medication and making decisions about dietary or lifestyle changes.

Chronic Obstructive Pulmonary Disease (COPD): Pulse oximeters and smart inhalers monitor pulse oxygen levels and medication use, helping predict flare-ups.

4. Postoperative Rehabilitation

After surgery, patients are often discharged home, but parameters such as their level of movement, pain level, and heart rate can be monitored remotely. This allows problems to be detected quickly (e.g., signs of infection) and makes sure that physiotherapy plans are followed.

4.1. Home Care of the Elderly and the Chronically Ill

Smart home sensors (location sensors, bed sensors, door/key sensors) can monitor daily activities and behavioral changes. For example, a sudden change in standing time may indicate an impending infection. This allows the elderly to continue to live independently while keeping them safe.

4.2. Clinical Studies (Clinical Studies)

RPM can dramatically improve clinical research. Instead of data collected once a month in traditional research centers, researchers can collect real-time, continuous, objective data from the practice group. This allows for a more accurate assessment of drug effectiveness and reduces the duration and costs of research [10].

4.3. Mental Health: Behavioral Monitoring for Depression and Anxiety

Mental health disorders, especially depression and anxiety, are considered to be one of the major reasons for disability in the world. However, traditional mental health services also have limitations like resource availability, stigma, and travel issues for traditional in-person consultations. IoT technology has revolutionary potential in providing RPM services to meet the unmet need in mental health by quantitatively and objectively monitoring mental health [11].

Technologies Used:

Physiological Data: Smartwatches and wearable technology can track heart rate variability (HRV) on a constant basis. This is an accurate physiological measure of stress and anxiety levels [12]. Digestion, sweating, and body temperature changes can also be indicators of emotional conditions.

Behavioral Data: Activity and Sleep: Accelerometers record daily steps, physical activity level, and sleep patterns (with periods of inactivity). Decreased physical activity and sleep disturbances are the main symptoms of depression [13].

Social Interactions: Social activity and communication frequency can be indirectly assessed using smartphone data (call logs, text messages, social media usage). Social isolation is an important risk factor for depression [14].

Voice Analysis: The microphone can (with user permission) analyze speech patterns, pitch, speech rate, and frequency. Monotonous speech or decreased speaking energy may be indicative of depressive episodes [15].

Location Data: GPS data helps to determine whether the patient leaves the house, strays away from their daily interests (e.g., not going to work) [16].

Advantages: Objective and Continuous Measurement: Instead of relying on the patient's subjective memories in traditional "once a month" therapy sessions, the therapist obtains objective, quantitative data about the patient's daily life [17].

Early Warning: Negative changes in behavior can be detected before the onset of a full depressive episode, allowing timely psychological support or therapy sessions to be scheduled [18].

Increased Self-Awareness: By seeing their own information, patients can better understand the relationship between stress and mood, and develop self-care skills. Evaluation of Treatment Effectiveness: The therapist can evaluate the effectiveness of a particular therapy method based on objective physiological and behavioral data of the patient.

4.4. Oncology: Home Monitoring of Cancer Patients

Oncology is one of the most complex and demanding areas where Remote Patient Monitoring (RPM) can fully deliver its potential. Cancer patients often undergo heavy treatment regimens (chemo- and radiotherapy), which cause numerous side effects such as weakness, pain, nausea and severe weakening of the immune system. The traditional model leaves patients alone between treatments, risking serious side effects that are often detected late and result in emergency hospital admissions. IoT-based RPM is transforming oncology care by moving the bulk of treatment to the patient's home, improving both quality and reducing hospital burden [19].

Symptom and Side Effect Management: Patients regularly record their symptoms (pain, nausea, fatigue, loss of appetite) through special mobile applications (ePRO - electronic Patient Reported Outcomes). Algorithms can analyze this data to predict serious side effects (eg, dehydration, neuropenia) [20].

5. Challenges, Limitations, and Solutions

Widespread adoption of RPM still faces a number of obstacles:

Data Privacy and Security: Health information is extremely sensitive

Cyber attacks pose a huge risk. Problem: Weak encryption, unauthorized data access, and data breaches.

Potential Solutions:
Strong Encryption: Encrypt data at rest and in motion (e.g., AES-256).
Instead, the ML model is trained (e.g., on the patient's smartphone) on local data, and only model updates (weights) are sent to the hub. This ensures that private data never leaves the device [21].

Technological Reliability and Accuracy

Problem: Sensor errors, signal loss, battery life limitations, and false alerts (both false negatives and false positives) can harm clinical reliability.

Potential Solutions:

Sensor Calibration and Validation: Routine calibration and validation of devices against clinically validated devices.

TinyML: This allows running machine learning models on small, low-power devices (such as the sensors themselves). This allows smarter sensors to filter out irrelevant data in situ, transmitting only significant events, thus reducing energy consumption and false alarms

Interoperability and Standardization

Problem: Thousands of IoT devices and software from different manufacturers create "islands of data" without standard communication protocols and data formats. This makes it difficult to easily share data from one system to another.

Potential Solutions:

Widespread adoption of industry standards such as FHIR (Fast Healthcare Interoperability Resources) can facilitate data sharing.

Infrastructure and the Digital Divide

Problem: Lack of reliable and fast internet in rural and remote areas limits the adoption of RPM. Potential Solutions: The growth of 5G technology assists in overcoming this issue by ensuring low latency and high speeds. On the other hand, the use of Edge Computing further eliminates the need for the internet.

Reception and Human Factors

Problem: Technophobia, difficult-to-use interfaces (particularly for seniors), and resistance to change may impede RPM system adoption. Potential Solutions: User-Centered Design (UCD), intuitive interfaces, and extensive training packages for patients and healthcare professionals.Future Trends and Development Directions. The future of RPM will be shaped by the integration of a number of rapidly developing technologies.

6. Deeper AI and Predictive Analytics

AI models will not only detect anomalies but also create personalized risk scores for the individual patient, moving towards hyper-personalized medical solutions. Combining multimodal data (sensory data, genetics, lifestyle) will provide more accurate predictions.

6.1. The Growing Role of Edge AI and TinyML

As computing power continues to improve and move closer to the sensor, devices can begin to carry out even more complex functions, like in-the-field classification of heart rhythm abnormalities via an EKG. This, in turn, continues to minimize power consumption and networking requirements.

6.2. Expanding Adoption of Federated Learning

As data privacy concerns increase, Federated Learning will become the standard paradigm for privacy-preserving AI, balancing the need for organizations to be able to create common models with sharing specific data.

6.3. Advanced Security Technologies As concerns about the security of Quantum Computing increase, Post-Quantum Cryptography (PQC) algorithms will be essential to protect data from future threats.

6.4. Integration of Extended (XR) and Metaverse

Future RPM systems may include Augmented Reality (AR/VR) interfaces where doctors can conduct virtual consultations and visualize patient data in an immersive 3D environment.

7. Conclusion

IoT-based Remote Patient Monitoring is a transformative force that is transforming healthcare systems from a reactive to a proactive and advanced model. It provides an unparalleled opportunity to improve patient outcomes, reduce costs, and increase patient satisfaction through real-time data collection, advanced analytics, and remote interactions. However, to realize this potential, we must address issues such as data security, technology reliability, technology integration, and human factors. In the future, the ongoing evolution and integration of technologies such as AI, Edge Computing, Federated Learning, and TinyML will revolutionize RPM into intelligent, safe, and comprehensive healthcare solutions. We must address the barriers to the adoption and use of such technologies by healthcare organizations, providers, and policymakers to ensure that high-quality, efficient, and person-centered healthcare is accessible to everyone.

Author Contributions

Fidan Arzumanova conducted the literature search and drafted the manuscript. Dr. Sabina M. Nobari supervised the study, provided critical guidance on content and structure, and reviewed the manuscript.

Conflict of Interest

The authors declare no conflicts of interest.

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