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<https://orcid.org/0000-0002-5274-0356>
tedqiqat1868@gmail.com

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aygun.b74@mail.ru

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Rovshan Humbataliyev

Azerbaijan State Marine Academy

Doctor of Mathematics

<https://orcid.org/0000-0002-9114-8953>

rovshangumbataliev@rambler.ru

Shahin Agazade

Baku State University

PhD in Pedagogy

<https://orcid.org/0000-0003-1594-9545>

seriye_allahverdiyeva@mail.ru

Farida Bayramova

Baku State University

<https://orcid.org/0009-0001-8413-692X>

feridamb1970@gmail.com

Umida Humbatali

Sumgayit State University

<https://orcid.org/0000-0002-8413-6193>

umidahumbatali@gmail.com

Information Technology-Based Model for Cancer Treatment

Abstract

Cancer is a serious global socio-health issue, and developing effective approaches for its treatment is of great importance. Advances in the field of information technology (IT) have significantly expanded the possibilities for personalizing and optimizing cancer treatment. This article presents an integrative model that enables the application of IT in cancer therapy. Key components of the model include artificial intelligence, big data analytics, telemedicine, and digital platforms. Compared to existing studies, the proposed model provides a personalized treatment strategy based on the synthesis of the patient's genetic, clinical, and lifestyle data. The results indicate that IT-based approaches not only improve the quality of life of patients but also enhance the efficiency of oncology management.

Keywords: *cancer, information technology, artificial intelligence, big data, telemedicine, oncology, digital health*

Introduction

Cancer is a group of complex diseases that develop in various organs and tissues under the influence of multiple genetic, epigenetic, and environmental factors. According to the World Health Organization (World Health Organization, 2023), cancer is the second leading cause of death globally, claiming millions of lives each year. Early diagnosis, personalized therapy, and continuous monitoring are essential components of effective cancer treatment.

Traditional medical approaches are primarily based on clinical symptoms and histological analyses. However, these methods often fail to reflect the genetic and molecular characteristics of individual patients. As a result, some treatment protocols are applied universally, yet their effectiveness varies due to individual differences. To address this limitation, innovative approaches in the field of information technology (IT) are being increasingly adopted.

In recent years, artificial intelligence (AI) and machine learning algorithms have begun to play a crucial role in early cancer detection and the optimization of treatment strategies (Lee, Kim, Park, 2020; Johnson, Gupta, 2022). Telemedicine has opened new avenues for delivering healthcare services to patients in remote regions (Zhang, Wang, Li, 2021).

Big data analytics allows for in-depth exploration of patient information and the development of individualized treatment plans (Smith, Johnson, Lee, 2019).

However, most existing studies apply these technologies in isolation, lacking systematic integration. For instance, Lee S., Kim J., and Park H. focused solely on the diagnostic process, while Zhang L., Wang Y., and Li Q. (Zhang, Wang, Li, 2021) examined the characteristics of telemedicine services. Smith A., Johnson M., and Lee K. (Smith, Johnson, Lee, 2019) discussed the challenges of big data analysis but gave limited attention to clinical implementation examples.

This paper introduces an integrative model that combines all these IT components. The aim is to develop personalized, effective, and adaptive treatment protocols based on the synthesis of the patient's genetic, clinical, and social data. Such an approach is expected to open a new chapter in the management of oncology.

The application of information technologies in cancer treatment has been explored in various studies. Lee S., Kim J., and Park H. (Lee, Kim, Park, 2020) confirmed the accuracy of artificial intelligence methods in the early diagnosis of cancer; however, their research provided limited insight into treatment optimization and patient monitoring. Johnson R. and Gupta N. (Johnson, Gupta, 2022) demonstrated the advantages of machine learning techniques in evaluating patient prognosis, yet they gave little attention to the implementation of such approaches in real clinical systems.

In the field of telemedicine, Zhang L., Wang Y., and Li Q. (Zhang, Wang, Li, 2021) proved the effectiveness of remote monitoring and patient supervision systems, but the integration of these systems with big data and artificial intelligence remains an unresolved issue. Smith A., Johnson M., and Lee K. (Smith, Johnson, Lee, 2019), in analyzing the use of big data in oncology, highlighted challenges related to data quality and management, yet offered only limited proposals for the implementation of an integrative model. In addition to these, mathematical modeling of cancer (Humbataliyev, Mamedov, 2024) and modeling of various related issues (Humbataliyev, Tagiyev, 2024; Humbataliyev, Humbatali, Humbatali, 2024; Humbataliev, 2014; Mirzoev, Humbataliev, 2011; Humbataliev, 2008) have also been studied.

Overall, the main shortcoming of existing work is the isolated application of technologies and the lack of data integration. The proposed model addresses this gap by consolidating all patient information into a unified platform, performing comprehensive analysis, and enabling dynamic adaptation of the treatment plan.

Research

Problem Statement. The implementation of a personalized treatment approach in oncology requires comprehensive analysis of the patient's genetic, epigenetic, clinical, and lifestyle indicators. At the same time, the real-time collection and evaluation of data during the treatment process is essential for therapy adaptation. One of the main challenges faced by modern healthcare systems is the effective management and analysis of this large-scale and heterogeneous data.

The primary objective of the problem is to develop an integrative, personalized, and adaptive model for cancer treatment by leveraging the capabilities of information technologies. This model should enable the synthesis of patient data from multiple sources into a unified database, its analysis through artificial intelligence algorithms, real-time monitoring via telemedicine, and the generation of an optimal treatment protocol.

Proposed Solutions. Enhancing the effectiveness of cancer treatment through information technologies requires a comprehensive and multidisciplinary approach. This approach consists of five core components: data collection and integration, big data analytics, artificial intelligence and machine learning, telemedicine and digital platforms, and the development of personalized treatment plans. The role and function of each component are explained in detail below.

Data Collection and Integration. A personalized approach to oncology treatment fundamentally relies on the systematic collection and integration of multi-source and heterogeneous data within a unified platform (Ritchie, et al., 2015). This includes clinical indicators, genetic and molecular profiles, radiological images, laboratory analyses, as well as social and environmental factors of the patient. For example, international initiatives such as The Cancer Genome Atlas (TCGA) have

established standards-based infrastructures for the large-scale collection and distribution of genetic data (Weinstein, et al., 2013).

Due to the heterogeneity of data, healthcare interoperability standards like HL7 and FHIR must be applied to ensure the seamless interaction of different systems (Mandel, et al., 2016). At the same time, data privacy is protected through legislation such as HIPAA and GDPR, thereby strengthening patient rights and data security.

Big Data Analytics. The analysis of collected data is carried out on big data platforms, where technologies such as Hadoop and Apache Spark are widely utilized (Dean, Ghemawat, 2008). Both static and dynamic analytical methods, including clustering, pattern recognition, and correlation detection techniques, are applied to refine molecular subtypes of cancer and assess treatment responses (Kourou, et al., 2015).

For instance, the use of genomic and proteomic data in big data analysis plays a crucial role in identifying biomarkers in cancer, which is essential for personalized therapy (Huang, et al., 2021).

Artificial Intelligence and Machine Learning. Artificial intelligence (AI) and machine learning methods have ushered in a new era in oncology diagnostics and treatment processes. Deep learning models analyze radiological and histopathological images with high accuracy to determine tumor localization and type (Esteva, et al., 2017). Furthermore, AI algorithms analyze patients' clinical indicators and genetic data to predict therapy effectiveness and disease prognosis (Kourou, et al., 2015).

For example, the IBM Watson for Oncology platform supports oncologists in developing personalized treatment plans and is applied in clinical practice (Somashekhar, et al., 2018). AI models also possess continuous learning capabilities, refining their predictions based on new incoming data.

Telemedicine and Digital Platforms. Telemedicine technologies significantly improve access to oncology services, especially for patients living in remote areas (Kruse, et al., 2017). Digital health platforms enable continuous monitoring of patient status and facilitate effective communication with healthcare providers. During the COVID-19 pandemic, telemedicine proved to be an essential tool in maintaining uninterrupted cancer treatment (Al-Shamsi, et al., 2019).

Additionally, digital platforms not only provide psychosocial support for patients but also increase adherence to treatment and ease clinical decision-making.

Development of Personalized Treatment Plans. Personalized treatment plans based on big data and AI analyses are designed by taking into account the patient's genetic, molecular, and clinical characteristics (Collins, Varmus, 2015). This approach not only improves therapy effectiveness but also helps prevent side effects and enhances patients' quality of life.

For instance, personalized PARP inhibitor therapy for carriers of BRCA1/2 gene mutations is successfully applied in cancer treatment (Lord, Ashworth, 2017). The system continuously monitors treatment progress and proposes adaptations according to the patient's condition, enabling a dynamic and adaptive therapy approach.

Advantages. The application of information technologies in cancer treatment enables multidisciplinary and innovative approaches. The main advantages of this approach are as follows:

Comprehensive Data Integration. Personalized therapy in cancer treatment is fundamentally based on the synthesis of data collected from various sources-including genetic, clinical, radiological, laboratory, and social factors (Ritchie, et al., 2015). This comprehensive integration facilitates more accurate diagnostics and the development of effective treatment strategies tailored to the unique profile of each patient. Thanks to modern information systems, unifying and standardizing data in a single database significantly enhances the quality of clinical decision-making (Mandel, et al., 2016).

Adaptive and Dynamic System. A key advantage of the system is the real-time adaptation of treatment according to the patient's condition. Artificial intelligence models and continuous monitoring analyze the patient's response to therapy and update treatment protocols as needed (Somashekhar, et al., 2018). This adaptive approach not only improves therapy effectiveness but also minimizes side effects and helps maintain the patient's quality of life.

Telemedicine Capabilities. Telemedicine technologies provide continuous and high-quality healthcare services to oncology patients, especially those living in remote and resource-limited areas (Kruse, et al., 2017). By eliminating time and geographical barriers between patients and specialists, telemedicine ensures treatment continuity and psychosocial support. Its importance was further highlighted during the pandemic (Al-Shamsi, et al., 2020).

Enhanced Prognostication by Artificial Intelligence. Artificial intelligence and machine learning methods demonstrate high accuracy in predicting treatment effectiveness and potential side effects (Kourou, et al., 2015; Esteva, et al., 2017). This supports the clinical decision-making process and allows for early-stage risk management. Moreover, the continuous learning capability of algorithms leads to the ongoing optimization of treatment strategies.

Efficient Resource Management. The application of information technologies assists in the effective management of clinical resources and reduces healthcare costs (Collins, Varmus, 2015). For example, personalized treatment plans and real-time monitoring reduce hospitalizations and the need for additional examinations. This enhances the sustainability of healthcare systems and optimizes resource utilization.

Conclusion

The integration of information technologies into various stages of cancer treatment marks the beginning of a new era in modern oncology. The proposed integrative model systematically and optimally organizes diagnosis, treatment, and monitoring processes by comprehensively considering the patient's genetic, molecular, clinical, radiological, and social determinants. This approach not only enhances the effectiveness of personalized therapy but also improves the patient's quality of life, reduces risks during treatment, and ensures efficient management of healthcare resources.

Various studies demonstrate that the application of information technologies significantly improves treatment outcomes for oncology patients (Esteva, et al., 2017; Somashekhar, et al., 2018). For example, prognostic models developed using artificial intelligence help increase the efficacy of chemotherapy and immunotherapy, while telemedicine ensures continuity of care and provides vital support for patients living in remote areas (Kruse et al., 2017; Al-Shamsi, et al., 2020).

Future research should prioritize clinical trials of the proposed integrative model across different types of cancer, adaptation to various patient groups, and the enhancement of legal and ethical aspects related to technology implementation. At the same time, establishing appropriate standards to ensure data privacy and security in the application of information technologies is essential.

Thus, the use of information technologies in cancer treatment can drive the development of multidisciplinary approaches and fundamentally improve the quality and effectiveness of oncology care.

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DOI <https://doi.org/10.36719/3104-4735/2/9-13>**Elshan Sultanov**

Azerbaijan State Marine Academy

PhD in Techniques

<https://orcid.org/0009-0002-0002-7038>elshen_sultanov@mail.ru

Integrated Digital Solutions in the Management of Ship Electrical Systems

Abstract

The article analyzes the impact of integrated digital control systems applied in the modern shipping industry on the operation of ship power plants. The advantages of the transition from traditional analog control systems to digital platforms are examined, in particular, the working principles of the power management system and integrated automation system are examined. The article also highlights the contributions of digital solutions to energy efficiency, fuel economy and ship safety. The main contributions of digital solutions to energy efficiency, fuel economy and ship safety are the optimal operation of generators as a result of automatic load balancing, the prevention of excess and unnecessary energy consumption, the early detection of faults that cause power loss and the collection of accurate statistical data on energy consumption. In this case, energy efficiency increases and equipment wear and tear decreases.

Keywords: *ship, electrical systems, power management system, digitalization, integrated, energy efficiency*

Introduction

Maritime transport remains the dominant force in the world economy and the backbone of the global supply chain, accounting for approximately 90% of global trade. However, in the 21st century, the maritime industry is undergoing a radical technological transformation under the influence of the "Industry 4.0" revolution (Sultanov, Jalilov, 2018). Modern ships are no longer simply vehicles for transporting goods, but rather complex engineering structures (floating power plants) with power measured in megawatts. In particular, the increase in electrically powered ships and the introduction of high-voltage systems have significantly complicated the structure of ship power (Patel, 2012).

Historically, in traditional shipping, power plants, navigation systems and cargo operations operated in an isolated, local mode. This fragmented approach limited information exchange, slowed down operational decision-making and increased the risk of accidents caused by the human factor. However, in the face of the challenges of the modern era, increasing energy demand, the global fuel crisis and the need to optimize operating costs, this approach requires a change (Fernandez, 2018).

Integrated digital solutions are a set of technologies that enable the control, monitoring and analysis of all electrical and electrotechnical systems on board a ship through a single digital platform. These solutions increase the safety and efficiency of ship operations by combining automation, information exchange and decision-making processes in a single center (Sultanov, Hasanov, Ismayilov, Mammadov, 2023).

Integrated digital solutions perform the following functions:

Automatic control of electricity generation and distribution, load balancing and energy efficiency improvement, early fault detection and warning systems, continuous monitoring of the condition of electrical equipment, collection of analytical data for technical service.

At the same time, environmental factors have begun to play a decisive role.

Stringent regulations such as the Energy Efficiency Design Index (EEDI) and the Carbon Intensity Index (CII) introduced by the International Maritime Organization (IMO) force ship owners to reduce carbon emissions and maximize energy efficiency. On the other hand, the optimization of ship crew numbers and the transition to the concept of the "autonomous ship" of the future have made the introduction of intelligent systems that minimize human intervention in management inevitable.

All these factors have made the implementation of "integrated digital solutions" a necessity. Thanks to advanced sensor technologies and real-time data analysis, ship electrical systems now operate as a single digital system (IMO International Maritime Organization, 2020). As the technical complexity of ships in modern maritime transport increases, the role of electrical systems for their safe, efficient and reliable operation is becoming increasingly important. Since traditional local control methods do not meet modern requirements, the concept of controlling ship electrical systems from a single digital center has become widespread in recent years. This approach is distinguished by its automation, digitalization and real-time monitoring capabilities. Ship electrical systems include energy production (generators), energy distribution (distribution boards), consumers (navigation equipment, engines, lighting, security systems) and backup energy sources. Each of these systems works in close interaction with each other, and any malfunction can seriously affect the overall operation of the ship. A single digital control center (SDCC) is an integrated platform that provides control, monitoring and analysis of all electrical and electrotechnical systems on board from a single center through software. This center is usually built on the basis of SCADA, PLC, IoT sensors and industrial network protocols (for example, Modbus, CAN, Ethernet).

Control from a single digital center performs the following main functions:

Real-time monitoring: Continuous monitoring of parameters such as voltage, current, frequency, load level. Automatic control: Load balancing, automatic connection and disconnection of generators. Early detection of faults: Prediction of potential accidents based on analysis of sensor data. Data archiving: Creation of a database for technical maintenance and analysis. Remote control and diagnostics: Possibility of controlling systems from the shore or bridge (Hassan, Amer, Williams, 2018).

The application of this approach creates a number of important advantages:

This approach contributes to increasing safety, improving energy efficiency, reducing operating costs, enhancing operational decision-making, and ensuring compliance with international standards.

However, the implementation of single digital control systems is also accompanied by certain difficulties. These include high initial investment costs, cybersecurity risks, the need to increase the qualification level of personnel, and integration problems with legacy systems. In the future, the management of ship electrical systems will be further improved with the application of artificial intelligence and machine learning technologies. Predictive maintenance, fully autonomous energy management, and the "smart ship" concept are considered the main development directions in this field (Jimenez, Kim, Minima, 2022). The main purpose of the article is to analyze the technical structure of controlling ship electrical systems from a single digital center, and to scientifically investigate the impact of this transition on energy efficiency, operational safety, and economic efficiency.

Research

Modern ship electrical system control is based on multi-level digital architectures. These systems typically consist of 3 main levels:

1. Area (This includes sensors, measuring transformers and actuators);
2. Management (Here information processing takes place. The main role is played by programmable logic controllers (PLC);
3. Monitoring and management (This is the level at which the operator monitors the process through the human-machine interface (HMI) and SCADA systems).

The basis of digital integration is considered to be the power management system. The power management system is a set of digital algorithms that control the generators of the ship's power plant without human intervention (Sultanov, Jalilov, 2018).

The main functions of the power management system are as follows:

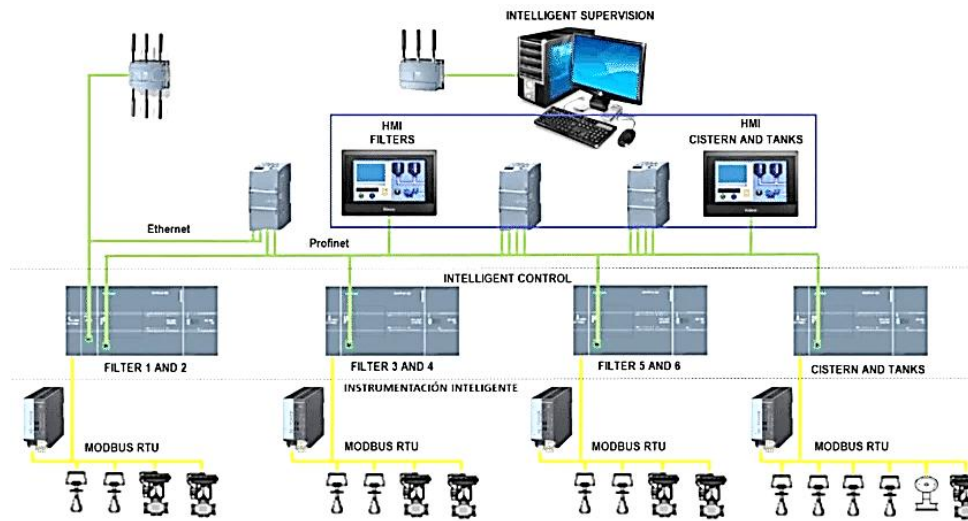


Figure 1. Block diagram of ship electrical power system automation

Load distribution: Equal distribution of active and reactive load between generators operating in parallel using digital controllers. This process is based on the static characteristic (droitness) of motor speed controllers (Wildi, 2014).

Modern digital controllers realize this dependence with the following linear equation:

$$f=f_0-k_p\cdot P$$

Here:

f – current network frequency (Hz);

f_0 – generator no-load operating frequency;

k_p – droop coefficient of the speed controller;

P – is the active power provided by the generator (kW).

To distribute reactive power and maintain voltage stability, the static characteristic of the automatic voltage regulator is used:

$$U=U_0-k_q\cdot Q$$

Where: U_0 – nominal voltage (V), k_g – voltage droop coefficient, Q – reactive power (kVar).

The digital control system automatically adjusts these coefficients (k_p and k_g), ensuring stable operation of generators of different power in a single network.

Automatic synchronization: The moment of connection of the generator to the network (matching the frequency, voltage and phase angle) is carried out by microprocessors with millisecond accuracy (Hasanova, Yusifbayli, 2023).

The image of the human-machine interface of the power control system in the ship's main switchboards is given in Figure 2.

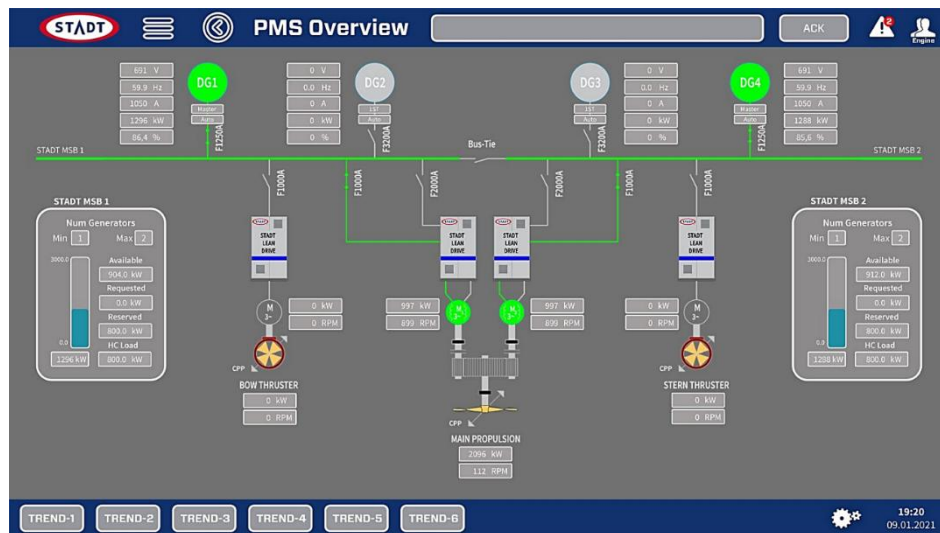


Figure 2. Image of human-machine interface in a modern control system

Opening of low-responsibility users: This function prevents the ship's power system from completely shutting down. If the operating generators cannot carry the load, the system automatically disconnects the tertiary generators from the network. Figure 3 shows the fuel consumption optimization graph of the ship's electrical power management system (Ismayilova, Mirzaeva, Ismiyeva, 2024).

Digital control not only means convenience, but also savings. While in traditional systems an additional generator was always kept running for backup, modern "Smart" systems predict load demand.

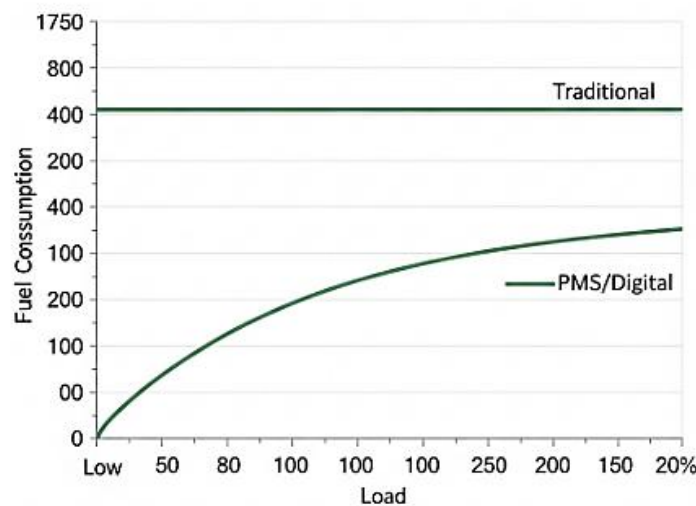


Figure 3. Fuel consumption optimization chart of the ship's electrical power management system

The graph below shows a comparison of fuel consumption with traditional and digital control. Integrated systems store all parameters (temperature, pressure, etc.). Thanks to "big data" analysis, engineers receive warnings before equipment fails. This minimizes the downtime of the ship.

Conclusion

The conducted analyses show that the application of integrated digital solutions in ship electrical systems is a fundamental approach transformation in the maritime industry. Digital power management systems (PMS) minimize specific fuel consumption and operating expenses (OPEX) by ensuring optimal operation of generators in accordance with the load schedule. Automated synchronization, active/reactive load sharing and intelligent load shedding functions increase the resilience of the network by eliminating risks arising from the human factor. These technologies directly contribute to the implementation of international environmental regulations (IMO EEDI/CII) limiting carbon emissions. In the future, the transition to fully autonomous marine energy installations with the integration of artificial intelligence is inevitable.

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DOI <https://doi.org/10.36719/3104-4735/2/14-18>**Peri Huseynova**

Nakhchivan State University

PhD student

<https://orcid.org/0009-0002-7021-7806>perihuseynova@ndu.edu.az**Nurtaj Rahimova**

Nakhchivan State University

<https://orcid.org/0009-0002-0718-1521>nurrehimli1@gmail.com**Sunay Gulmaliyev**

Nakhchivan State University

<https://orcid.org/0009-0008-6662-4023>sunayhuseyinli9@gmail.com

Eco-Friendly Functional Modification of Biopolymers for Technological Applications

Abstract

The transition toward sustainable material technologies has driven increasing attention to biopolymers as environmentally benign alternatives to conventional synthetic polymers. Owing to their renewable origin and biodegradability, biopolymers present a viable pathway for reducing environmental burdens in multiple technological domains. Nevertheless, intrinsic drawbacks such as limited mechanical robustness, moisture sensitivity, and restricted functional performance often constrain their direct use. Consequently, eco-friendly functional modification has become a central strategy for enhancing the technological relevance of biopolymers.

This article critically examines contemporary approaches employed to modify biopolymers using environmentally compatible methodologies. Emphasis is placed on chemical and physical modification routes that enable property optimization without undermining sustainability principles. In addition, recent progress in the development of biopolymer-based nanocomposites is discussed, highlighting their improved mechanical integrity and multifunctional performance in advanced applications, including packaging and biomedical systems. The interplay between polymer structure and functional behavior is analyzed to elucidate how targeted modifications can improve barrier efficiency, surface characteristics, and active functionalities such as antimicrobial or UV-protective properties. Furthermore, the environmental benefits of biopolymers are evaluated through biodegradability, renewability, and life cycle assessment perspectives. The contribution of modified biopolymers to circular economy frameworks, along with existing technological challenges and future research needs, is also addressed.

Keywords: *biopolymers, eco-friendly functionalization, green materials, nanocomposites, sustainable technology, circular economy*

Introduction

The escalating environmental challenges posed by widespread use of petroleum-based polymers have intensified the search for sustainable alternatives in material science. Biopolymers, derived from renewable sources, offer a promising solution due to their biodegradability and reduced ecological footprint. Their integration into technological applications presents an opportunity to mitigate environmental impact while promoting sustainable development (Wei, 2025).

Despite their potential, native biopolymers often face limitations that restrict their direct applicability in advanced technological systems. These limitations include insufficient mechanical robustness, high moisture sensitivity, and limited functional versatility.

Addressing these constraints requires strategic approaches that can enhance performance without compromising environmental benefits (Rebolledo-Leiva, 2023).

Eco-friendly functional modification has emerged as a central strategy for overcoming these challenges. By employing environmentally compatible methods, biopolymers can be tailored to meet specific technological requirements, thus bridging the gap between sustainability and practical utility (Gudina, 2020).

The present article aims to provide a technology-oriented perspective on eco-friendly modification of biopolymers. It focuses on strategies for enhancing functional performance, the relationship between structural properties and application potential, and the broader implications for environmental sustainability and circular economy integration (Venkateshwar, 2024).

Research

Environmentally Compatible Modification Approaches. In recent years, biopolymers have emerged as strategic materials in the pursuit of sustainable technological solutions. Their derivation from renewable resources positions them as promising substitutes for fossil-based polymers, particularly in applications requiring reduced environmental impact (Jalil, 2024). However, the performance limitations of unmodified biopolymers require targeted modification strategies to meet technological standards (Sultanov et al., 2023). Eco-friendly modification techniques generally fall into chemical and physical categories. Chemical approaches involve the selective introduction of functional groups using milder, low-toxicity reagents, enabling improvements in flexibility, thermal endurance, and mechanical performance while preserving biodegradability (Cherian, 2023). Physical modification strategies, including polymer blending and composite fabrication, offer an alternative route by exploiting intermolecular interactions to adjust material properties without permanent chemical alteration (Mehta, 2024). From an industrial perspective, these methods are advantageous due to their relative simplicity and scalability.

Beyond conventional modification routes, the integration of nanoscale components into biopolymer matrices has attracted considerable attention. Such biopolymer-based nanocomposites exhibit enhanced strength, stability, and functional versatility, allowing their application in technologically demanding environments (Sharma, 2025). The combination of biodegradability and improved performance has led to their classification as green nanocomposites, underscoring their relevance in eco-conscious material design (Khan, 2025).

Structural Characteristics and Functional Performance. The response of biopolymers to modification processes is inherently linked to their molecular and supramolecular structure. Attributes such as hydrophilic–hydrophobic balance, crystallinity, and chain mobility govern the effectiveness of functionalization strategies. Modifying these structural parameters can significantly enhance surface wettability, mechanical resistance, and barrier properties, thereby broadening the range of viable technological applications (Biswal, 2024).

Functional adaptation through modification enables biopolymers to acquire properties tailored to specific end uses. The incorporation of antimicrobial functionalities or UV-shielding capabilities, for example, has proven particularly valuable in packaging, textile, and surface-coating technologies (Daget, 2025). Such tunability illustrates the potential of biopolymers to serve not merely as passive materials but as active components within advanced technological systems.

Environmental Benefits and Sustainability Assessment. The ecological advantages of biopolymers are primarily associated with their biodegradability and renewable feedstock origin. These characteristics contribute to reduced fossil fuel consumption and lower greenhouse gas emissions when compared to conventional plastics (Mohan, 2024). In short-life-cycle applications, such as food packaging, biopolymers can substantially mitigate long-term environmental pollution (Jayakumar, 2020).

To ensure that these benefits are realized in practice, life cycle assessment (LCA) has become an indispensable evaluation tool. LCA studies provide insight into the environmental footprint of biopolymer production, use, and disposal, demonstrating that appropriately engineered biopolymer

systems can reduce waste generation and ecosystem contamination across their entire life span (Edo, 2025).

Biopolymers and Circular Economy Integration. The alignment of biopolymers with circular economy principles represents a major driver for their technological adoption. Their capacity for biological degradation and reintegration into natural cycles minimizes persistent waste and alleviates pressure on non-renewable resources (Getahun, 2024).

As a result, biopolymers are increasingly regarded as key enablers of resource-efficient material cycles.

Owing to their structural diversity and functional adaptability, biopolymers have found application across a broad spectrum of industries, including food packaging, pharmaceuticals, and construction materials (Kalemtas, 2025).

In particular, biodegradable packaging solutions exemplify how biopolymers can replace single-use plastics while supporting circular economy objectives and sustainability policies (Wang, 2025).

Challenges and Future Outlook. Despite their promise, several obstacles continue to limit the widespread industrial implementation of biopolymers. Economic factors, such as production cost, along with technical issues related to material consistency and processing, remain significant challenges (Boopathi, 2024).

Addressing these limitations will require advances in modification chemistry, composite engineering, and large-scale manufacturing technologies.

Future progress in biopolymer-based systems will depend strongly on interdisciplinary collaboration among chemists, materials scientists, engineers, and industrial stakeholders. Such cooperation is essential for translating laboratory innovations into commercially viable, environmentally responsible technologies (Fodor, 2025).

Conclusion

The present study demonstrates that eco-friendly functional modification of biopolymers is essential for enhancing their applicability in technological systems. Through chemical, physical, and nanocomposite-based approaches, biopolymers can be tailored to improve mechanical properties, barrier efficiency, and functional characteristics such as antimicrobial activity and UV protection. These modifications enable biopolymers to meet diverse industrial demands while preserving their environmental advantages.

Biopolymers' inherent biodegradability and derivation from renewable resources allow their integration into sustainable practices, contributing to reduced environmental impact, lower carbon footprint, and alignment with circular economy principles. By adopting these materials, industries can replace conventional synthetic polymers with environmentally compatible alternatives, thereby promoting resource efficiency and waste reduction.

Despite these benefits, challenges such as production scalability and material performance variability remain. Addressing these limitations will be crucial for expanding the practical use of modified biopolymers. Continued innovation in functional modification techniques and a clear understanding of the relationship between structure and performance will be key to unlocking their full potential.

In summary, eco-friendly functional modification transforms biopolymers into versatile, high-performance materials suitable for sustainable technological applications. Their development supports environmental preservation, resource-efficient material use, and the advancement of circular economy objectives, positioning biopolymers as strategic components for future eco-conscious technologies.

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DOI <https://doi.org/10.36719/3104-4735/2/19-25>**Rovshan Taghiyev**

Nakhchivan State University

<https://orcid.org/0000-0002-3682-8788>

rovsentagiyev@ndu.edu.az

The Role of Information Technologies in Organizations: Impacts on Management, Decision-Making, and Organizational Efficiency

Abstract

In the competitive environment of the digital era, information has become a strategic asset that must be continuously produced, managed, and transformed into organizational value. This study examines the use of information technologies (IT) in organizations, and analyzes their effects on organizational structures, business management, decision-making processes, and operational efficiency. Drawing on the evolution of information systems from basic record-keeping to management information systems and decision support systems, the research highlights how IT enables faster and more accurate decisions, improved communication and collaboration, and the removal of geographical limitations through digital and networked operations. The study also emphasizes that successful digital transformation is not solely technological; it requires strategic leadership, cultural adaptation, and the development of employee competencies to reduce resistance and enhance performance outcomes. Furthermore, the paper discusses IT's role in productivity gains, cost reduction, innovation, and competitive advantage, while addressing the workforce implications of automation, artificial intelligence, and emerging digital professions. Overall, the findings suggest that organizations integrating IT effectively across all levels are better positioned to increase efficiency, respond to customer demands, and sustain competitiveness in rapidly changing markets.

Keywords: *information technologies, digital transformation, decision-making, business efficiency*

Introduction

In the competitive conditions of the digital era, information has evolved from being merely a supportive element to a strategic asset for organizations. The continuously changing and renewable nature of information necessitates that organizations generate new knowledge daily, enhance their learning capacities, and translate this learning into actionable behavior. Therefore, contemporary businesses are compelled to address learning and knowledge management at the organizational level with the aim of creating a more agile, productive, and capable workforce.

The successful integration and effective operation of knowledge management within organizations largely depend on the presence of an appropriate technological infrastructure. Information technologies accelerate the collection, processing, storage, distribution, access, and control of information, thereby strengthening decision-making processes, enhancing operational efficiency, and enabling faster responses to customer demands. Historically, the role of information systems in organizations has expanded from fundamental functions such as record-keeping and accounting to management information systems, decision support systems, and internet-based business models. This evolution has facilitated significant transformations in communication, collaboration, innovation, and overall organizational performance.

This study aims to examine the use of information technologies in organizations and their impact on organizational structures and management processes. The research emphasizes the contribution of information technologies to decision-making, their role in enhancing business efficiency and competitive advantage, and the importance of considering digital transformation not only as a technological shift but also in terms of human resources and organizational culture.

Research

The Use of Information Technologies in Organizations. In the competitive conditions of the digital era, the value of information as a strategic instrument is highlighted by its constantly evolving nature and the necessity for continuous production. In this context, organizations are expected to possess the capability to generate new knowledge daily, alongside mechanisms for learning and developing new behaviors. The strategic significance of learning stems from the need for a workforce that is smarter, more agile, and more productive. While in the traditional economy the attributes of industrial workers showed little variation, in the new economy the learning coefficient of tasks has increased rapidly (İnce, 2023).

Integrating and operationalizing knowledge management within organizations is only possible through the establishment of the appropriate technological infrastructure. Hence, the necessity of information technologies that automatically facilitate the collection, processing, distribution, access, and control of information cannot be denied (Ceyhun & Çağlayan, 1997).

Since the 1950s, when information technologies began to be integrated into organizations, numerous studies have been conducted by academics and industry representatives to evaluate their potential impacts. While the opportunities that information and information technologies offer to organizations are widely acknowledged in the global literature, their effects on organizational performance remain a subject of debate, with limited empirical investigation. Today, organizations that implement information and information technologies across all levels, ensuring their adoption and active use, are better positioned to compete and achieve success. The time-saving benefits of using information technologies in organizations are universally recognized (Turunç, 2016).

Until the 1960s, the use of information systems in organizations was limited to processing accounts, maintaining records, and bookkeeping. With the development of Management Information Systems (MIS) in the 1960s, a new role was introduced, providing managerial-level users with pre-defined reports necessary for decision-making. By the 1970s, it became apparent that this MIS role was insufficient for addressing managerial decision-making needs, leading to the development of Decision Support Systems (DSS) for managers. These systems function by “transforming specific problems encountered by managers in the workplace into fundamental decision-making techniques used by managers” (Ünüvar, 2006).

In the 1980s, new roles for information systems were established, including microprocessor application software, telecommunications, executive information systems, and expert systems. These applications enabled managers to generate or access the information they required directly, rather than relying solely on different organizational units, and to store critical information necessary for operational activities in the desired format and content. The growth of internet use in the 1990s led to significant changes in global ventures and business operations, particularly in communication and collaboration. The adoption of innovations in information technologies within organizations enhanced inter-organizational communication and collaboration, improved the efficient use of time, overcame geographical limitations, and facilitated substantial progress in effectiveness, productivity, and innovation (Ünüvar, 2006).

Information Technologies and Changing Organizational Structures. Since humans began inventing, discussions about technology and its impact on the future have persisted. By the late 19th century, debates on the positive and negative effects of technology became more pronounced. In the 21st century, these discussions focus on the idea that rapid technological progress is driving humanity toward a “post-human” era, with both utopian and dystopian perspectives (Vural, 2013).

Utopians view information technologies as beneficial, predicting the rise of an information society that will transform social relations, work life, education, political structures, and daily life. Global communities, remote work, smart machines, and digital commerce are among the envisioned changes. From an organizational perspective, the role and importance of information technologies have evolved over time. Initially focused on record-keeping and accounting, by the 1970s organizations required decision support systems, and by the 1980s, users could access needed information directly (Özden, 2015). Organizations now rely on continuously updated technologies and information

management systems to operate efficiently. Information promotes openness and transparency, transforming individuals and organizations into active, networked units rather than isolated points (Erkan, 1998).

The Impact of Information Technologies on Business Management. Businesses are increasingly compelled to adopt information and communication technologies (ICT) due to competitive pressures in the global market. This adoption can lead to cost savings, improved service quality, and enhanced competitive advantage. ICT usage allows organizational units, such as human resources and finance, to operate digitally, simplifying workflow and monitoring (Evans, 2007).

Managing change is closely linked to human resources. For technological transformations to contribute effectively, employees must develop the necessary knowledge, skills, and work approaches. Without enhancing employee competencies, technological changes alone are unlikely to improve organizational performance. In other words, employees' productivity and innovative ideas directly influence organizational outcomes, making human resource adaptation as critical as technological implementation (Berisha-Shaqiri, 2014).

According to Rogers, digital transformation is more strategic than purely technological. While infrastructure updates are important, strategic thinking and digital leadership are central to successful transformation. Managers who embrace this wave of change and guide their organizations toward innovation are more likely to succeed in technology management (Rogers, 2016; Çoruh, 2019).

Some developments that have forced business management to change through information technologies are as follows (İraz & Şimşek, 2004):

- The increasing pace of technological change making existing systems quickly obsolete,
- Changes in competition styles, intensified competition, and the pressure on companies to meet cost and quality standards in order to achieve competitive advantage in the industry,
- Customer dissatisfaction with poor service and low quality, along with evolving and increasing customer demands,
- Organizations' desire to adapt to multicultural environments, necessitating changes in human resources policies and practices to attract and employ diverse talent due to workforce transformations,
- Demographic and social changes in developed countries, including the decreasing proportion of young people in the population, which places continuous pressure on businesses.

Digital transformation in businesses is not limited to technology; it primarily concerns organizational culture and workforce. Technological transformation encompasses not only infrastructure but also organizational culture and human resources. Existing employees may often resist acquiring new skills. Anticipating this resistance and planning measures during the decision-making process allows managers to implement the transformation more effectively (Banger, 2017).

The Impact of Information Technologies on Decision-Making. Effective decision-making requires the use of reliable, accurate, and complete information. To make sound decisions, organizations must first identify the elements of the decision-making process and the factors that influence decision behavior. Within the organization, the following steps should be followed: the situation requiring a decision must be determined, all necessary data should be collected, the available information must be analyzed, alternative solutions researched, their probabilities assessed, compared, and finally, the most suitable option selected and implemented (Çavuş, 2008).

Today's managers make a wide variety of decisions in dynamic and rapidly changing environments. The rationality and accuracy of these decisions largely depend on the diversity and reliability of the information available to decision-makers.

Modern organizations must consider multiple variables and parameters that can affect ongoing activities in their decision-making processes. Otherwise, decisions based solely on an individual manager's knowledge and experience can lead to significant organizational losses (Emhan, 2007).

The inclusion of management information systems (MIS) in organizational decision-making processes provides several benefits (Sarihan, 1998):

- Increases operational efficiency by making routine tasks faster and less costly.
- Shortens processes in sectors such as banking and tourism, enabling better customer service through computerized systems.
- Supports the development of information-based product lines, as information itself is both an input and a product.
- Provides a competitive advantage for organizations where information is effectively processed and utilized in production.
- Facilitates the identification and exploitation of new market opportunities.
- Saves time and labor within the organization, promoting standardization and institutionalization.

The Impact of Information Technologies on Business Efficiency. In the knowledge economy, information and technology applications are among the most important production resources for both businesses and national economies. Labor, as a production factor, is no longer based solely on physical strength and skills, as in industrial economies, but also on the knowledge it contributes to production. Businesses require this knowledge-based labor to strengthen their operations (Yıldırım, 2004). Productivity increases are achieved through higher quality and lower-cost production, with information technologies and their proper use being primary factors influencing efficiency (Alkadi et.al., 2012).

The active use of information technologies in businesses is essential for focusing on the knowledge economy, increasing added value, and creating new business areas (Shahin & Topal, 2016). The development of information technologies continuously influences production, quality, service, and time factors, compelling organizations to adapt. Their use has led to structural changes within organizations, enabled entry into new markets, created new methods for product and service delivery, and enhanced process efficiency (Albadvi et.al., 2007).

Research indicates that businesses actively utilizing information technologies adapt more easily to market changes, achieve higher value and benefits compared to competitors, and gain a significant competitive advantage (Çoruh, 2019).

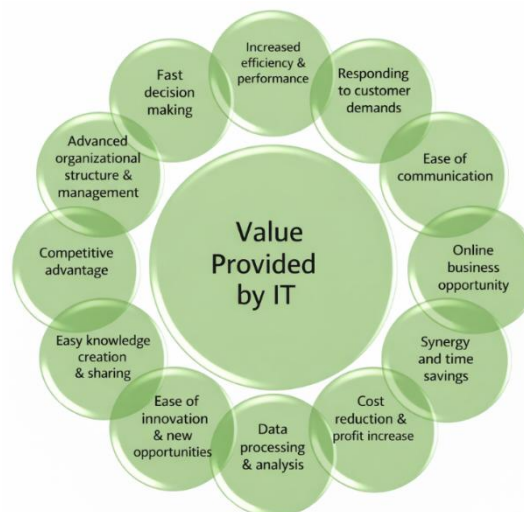


Figure 1: Values Provided by Information Technologies

Information technologies (IT) tend to dominate production and business processes by using tools such as computer-aided design and manufacturing, telecommunications networks, expert systems, distributed knowledge-based organizations, inter-organizational information systems, and multimedia systems. Companies adopting new IT systems are more likely to sustain their operations (Dulkadir & Akkoyun, 2013).

Regarding human resources, the rise of robotics and artificial intelligence is expected to shift individuals toward roles demanding greater creativity and innovation. Education systems must equip future generations with 4C skills critical thinking, collaboration, communication, and creativity to prepare them for this evolving workforce, aligning with the demands of Industry 4.0 (Cengiz, 2019).

Research in the United States highlights the economic benefits of IT investments: for every \$1 invested in IT, companies can expect a \$2 return, with productivity increases reaching up to 80%. The World Economic Forum's Future of Jobs Report (2020) indicates that nearly 50% of surveyed companies planned workforce reductions in automated roles by 2022, 38% planned to increase staff based on productivity gains, and over 25% anticipated new job openings due to automation growth (Erdoğan et.al., 2021).

Although the demand for existing professions such as electronic engineering, software development, and technology engineering is expected to continue in the coming years, it is also anticipated that new job roles will emerge, including (Ertürk, 2021):

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| – <i>Industrial Solution Architect</i> | – <i>Data Analytics Specialist</i> |
| – <i>Cloud Computing Specialist</i> | – <i>Application Software Developer</i> |
| – <i>3D Printing Engineer</i> | – <i>Market Research Analyst</i> |
| – <i>Wearable Technology Specialist</i> | – <i>Blockchain Specialist</i> |
| – <i>Solar Energy Engineer</i> | – <i>IT/IoT Solution Architect</i> |
| – <i>Cybersecurity Specialist</i> | – <i>Network Engineer</i> |
-

Alongside these emerging professions, it is also projected that certain jobs may decline or even disappear due to the impact of information technologies. According to the World Economic Forum (2018), while 71% of current jobs existed in 2018, this figure is expected to decrease to 52% by 2022, with 48% of roles being integrated into automation processes (Erdoğan et.al., 2021). The professions anticipated to decline or vanish as a result of digital transformation include (Gökcalp et al., 2019):

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| – <i>Secretary/Administrative Assistant</i> | – <i>Cashier</i> |
| – <i>Assembly Line Worker</i> | – <i>Driver</i> |
| – <i>Machine Operator</i> | – <i>Personal Financial Advisor</i> |
| – <i>Logistics, Cargo, and Shipping Agent</i> | – <i>Courier</i> |
| – <i>Travel Agent</i> | – <i>Farmer</i> |
| – <i>Tour Guide</i> | – <i>Security Guard</i> |
| – <i>Accountant</i> | – <i>Call Center Operator</i> |
| – <i>Bank Clerk</i> | – <i>Laboratory Technician</i> |
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Developments in information technologies not only offer organizations new opportunities to enhance their competitive positioning in the market, but also reduce costs associated with system licensing and the lack of qualified workforce or technological infrastructure. In this context, organizations that effectively utilize information technologies can achieve increased productivity, reduce costs, develop new products, services, and processes, and gain a competitive advantage over their rivals (Karahan & Bürkek, 2022).

Conclusion

This study demonstrates that information technologies (IT) in organizations are not merely tools for accelerating operational processes, but have become strategic assets that directly impact decision-making, efficiency, innovation, and competitive advantage. An examination of the historical development of information systems reveals a transformation from basic functions such as record-keeping and accounting to management information systems and decision support systems. This evolution enables managers to access accurate information more quickly, rendering processes more

rational and measurable. Consequently, organizations benefit from time and labor savings, cost reductions, improved service quality, and strengthened institutional standardization.

The findings indicate that the success of digital transformation is not solely dependent on technological infrastructure investments; human resources, organizational culture, and leadership are equally critical determinants. Developing employees' competencies to adapt to new systems, anticipating potential resistance, and implementing planned change management processes are essential. Otherwise, technology investments alone cannot guarantee the expected performance improvements.

Furthermore, the widespread use of IT supports more networked, flexible, and transparent organizational structures, facilitates access to new markets, enables process redesign, and accelerates innovation. The rise of robotics, artificial intelligence, and automation is reshaping the labor market, reducing the relevance of certain professions while highlighting new roles in areas such as data analytics, cybersecurity, and cloud computing. Therefore, organizations must align their IT strategies with education and talent management policies that develop the competencies required for the future workforce.

In conclusion, organizations that effectively adopt information technologies across all organizational levels and integrate this transformation with strategy, culture, and human capital are better positioned to achieve cost advantages, enhanced efficiency, stronger decision-making capabilities, and sustainable competitive superiority. Accordingly, IT investments should be approached not merely as technical modernization, but as part of a holistic management strategy that supports organizational learning and transformation.

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DOI <https://doi.org/10.36719/3104-4735/2/26-29>**Huseyn Gasimov**

Nakhchivan State University

PhD in Techniques

<https://orcid.org/0000-0002-3714-875X>huseynqasimov@ndu.edu.az**Rugayyaxanim Garibzada**

Nakhchivan State University

Master's student

<https://orcid.org/0009-0001-4962-918X>ruqeyyexanim202027@icloud

Deep Learning versus Traditional Antivirus Software

Abstract

Cybersecurity has become increasingly complex, with traditional antivirus software struggling to keep up with modern threats such as zero-day exploits and advanced persistent threats (APTs). While traditional methods, including signature-based detection and heuristic analysis, remain effective against known malware, they fall short in detecting new or sophisticated attacks. The rapid evolution of cyberattacks, as well as the emergence of polymorphic and metamorphic malware, severely reduces the effectiveness of traditional defense methods. Because this type of malware changes its code structure with each execution, it easily manages to evade signature-based systems by confusing them. On the other hand, deep learning-based security systems leverage artificial intelligence to analyze patterns and behaviors, providing superior detection of previously unseen threats. These systems analyze large volumes of telemetry data, monitor behavioral changes in real time, and identify subtle patterns that traditional methods cannot detect. It is precisely these capabilities that make them an indispensable component in proactive defense strategies. However, deep learning systems require more computational resources and are vulnerable to adversarial attacks. A hybrid approach that combines traditional antivirus methods with AI-driven solutions offers a promising strategy to enhance cybersecurity defenses, providing comprehensive protection against a wider range of cyber threats.

Keywords: *cybersecurity, deep learning, antivirus software, machine learning, threat detection*

Introduction

Cybersecurity threats have evolved significantly over the years, with cybercriminals using sophisticated methods to bypass traditional defense mechanisms. Conventional antivirus software primarily relies on signature-based detection, where a file's attributes are compared to a predefined database of malware signatures. Malware developers often focus on information niches with a large number of users (Berrios, 2025, p. 8). Malware detection methods are divided into three types: static, dynamic and hybrid (Bensaoud, 2024, p. 4). In addition, heuristic analysis is used to detect suspicious behavior that is indicative of malware, even if the specific threat has not been previously identified. However, because both signatures and heuristic approaches are based on static characteristics, they cannot fully encompass the dynamic and changing nature of cyberattacks, and are consequently easily evaded by attackers. Despite these capabilities, traditional antivirus solutions struggle to combat modern threats such as zero-day exploits, polymorphic malware, and advanced persistent threats (APTs). Now malware uses clever tactics to avoid antivirus protection (Zakaria, 2025). These sophisticated forms of cyberattacks are constantly evolving, making it difficult for signature-based antivirus software to keep up. In addition, the increasing volume of new malware samples being created every day further exacerbates the limitations of traditional methods.

Because polymorphic and metamorphic malware can automatically change its code, traditional antivirus systems have difficulty distinguishing the different variants of the same malware, which significantly reduces the detection rate of threats. In contrast, deep learning-based security systems use artificial neural networks (ANNs) to dynamically analyze and classify malware. Unlike signature-based antivirus software, deep learning models do not rely solely on predefined patterns. Instead, they are trained on a large database of good and malicious code, allowing them to recognize complex patterns and behaviors associated with cyberthreats. This capability allows deep learning systems to identify and mitigate new and previously unknown attacks without requiring frequent updates to the malware signature database (Patel, 2022; Zhang, 2023).

Traditional antivirus software. Traditional antivirus software uses a combination of signature-based detection, heuristic analysis, and behavioral monitoring to identify and neutralize malware threats. Signature-based detection works by scanning files and processes against a database of known malware signatures. If a match is found, the antivirus software blocks or quarantines the threat. While this method is effective against known malware, it struggles to detect new and modified threats that have not yet been cataloged (Anderson, 2020). Many antivirus programs incorporate heuristic analysis to increase their detection capabilities. This approach examines file attributes, code structure, and runtime behavior to identify potentially malicious activities. While heuristic analysis provides a degree of protection against unknown threats, it is prone to false positives, where legitimate files may be flagged as malicious. Another common feature in traditional antivirus solutions is sandboxing, a technique that executes suspicious files in an isolated environment to observe their behavior before allowing them to run on the system. While effective, sandboxing can be resource-intensive and slow, limiting its practical use in real-time threat detection (Bishop, 2003).

Deep Learning-Based Security Systems. Deep learning improves cybersecurity by using artificial intelligence to analyze large amounts of data and identify malicious patterns. Unlike traditional antivirus solutions that rely on predefined signatures, deep learning models use neural networks to detect anomalies and suspicious behavior. These models are trained on a large database containing a variety of malicious and malware samples, allowing them to recognize previously unseen threats based on their properties and behaviors (Patel, 2022). Deep learning-based security systems use techniques such as behavioral analysis, anomaly detection, and real-time monitoring. Behavioral analysis involves studying the actions of files and programs to determine whether they exhibit malicious intent. Anomaly detection focuses on identifying deviations from normal system behavior that could indicate a cyberattack. These techniques allow deep learning models to adapt and improve over time, making them more effective at identifying complex threats than traditional antivirus software. These systems can also analyze large datasets in real time by automating behavioral model analysis, detecting the execution of suspicious activities in advance, and minimizing the spread of attacks. Because deep learning models analyze behavior rather than relying on known signatures, they can identify suspicious activity even without prior knowledge of a specific malware strain. Deep learning models also enable us to learn from examples of polymorphic and metamorphic malware to predict future attacks and create adaptive defense strategies. However, deep learning-based security systems are not without their challenges. Training and deploying deep learning models require significant computational resources, making them more demanding than traditional antivirus software. In addition, adversarial attacks, in which cybercriminals manipulate input data to trick AI models, are a growing concern in AI-based cybersecurity (Zhang, 2020).

Traditional Antivirus and Deep Learning Security. Traditional antivirus software and deep learning-based security systems each have their strengths and weaknesses. Traditional antivirus solutions are lightweight, reliable, and effective against known malware. They demonstrate high compatibility with common operating systems and applications and have a minimal impact on system resources, making them advantageous for small and medium-sized enterprises.

However, they require frequent updates and struggle to combat new and sophisticated threats. In particular, zero-day attacks, polymorphic malware, and advanced persistent threats (APTs) severely

reduce the effectiveness of traditional antivirus software, as these attacks bypass known signature patterns from the outset to target the system (Chen, 2021, pp. 101-119).

On the other hand, deep learning-based security systems offer superior detection of zero-day threats, adaptability, and improved accuracy in identifying malicious activities. By analyzing large datasets, these systems model behavioral patterns, detect suspicious activities in advance, and can block previously unseen attacks. The adaptive learning capability of artificial intelligence enhances proactive defense against threats (Li, Zhao, 2020).

However, they require higher computing resources and expertise to implement effectively. The construction and training of deep learning models require powerful GPU and CPU resources, and expert knowledge in cybersecurity and the ethical use of data is also important for the models to function properly.

Emerging Threats and the Role of Hybrid Defense Models. As cyberthreats continue to evolve, attackers are increasingly using machine learning (ML) and artificial intelligence (AI) to circumvent traditional security mechanisms. For example, polymorphic malware can dynamically change its code and appearance, making it difficult to identify signature-based detection systems. Polymorphic malware generates a different code structure with each new execution, which delays detection by traditional antivirus signatures and also reduces the system's level of protection (Kazimov, 2020, pp. 45-47). In addition, AI-driven attacks can mimic human-like behavior, which can evade traditional heuristic and behavioral detection methods. AI-powered bots can mimic human behavior, including nuances such as keyboard rhythm and browser activity, which causes traditional detection systems to be fooled. These developments highlight the importance of adopting advanced security models such as deep learning to stay ahead of cybercriminals. Hybrid defense models that combine AI and traditional antivirus methods are becoming more relevant in this context. Deep learning models play a critical role in proactive security by identifying subtle patterns in large datasets, enabling the detection of previously unseen attacks (Hasanov, 2021, pp. 112-115). These models leverage the strengths of both approaches to create a more robust defense. AI can detect new and sophisticated attacks by analyzing large malware datasets, while traditional methods provide basic defense against known threats. In addition, such systems can leverage collaborative intelligence, where threat intelligence can be integrated from multiple sources to improve overall detection accuracy and response speed. Hybrid systems provide initial defense with signature-based filtering, while AI performs deeper behavioral analysis and minimizes defense gaps (Gasimova, 2020, pp. 59-63).

The Future of Cybersecurity: Integrating Traditional and AI-Based Approaches. The future of cybersecurity will likely involve a hybrid approach that combines traditional antivirus methods with AI-driven threat detection. Many cybersecurity firms are developing integrated solutions that use both signature-based detection for known threats and deep learning models to identify emerging threats.

This combination provides comprehensive protection while minimizing the limitations of each individual approach. As cyber threats continue to evolve, organizations and individuals must adopt multi-layered security strategies. By integrating deep learning alongside traditional antivirus solutions, cybersecurity defenses can be more robust, adaptive, and effective in mitigating cyber risks. (Aliyev, 2019, pp. 78-81).

Conclusion

In the modern era, cyber threats are becoming increasingly complex, and traditional antivirus software struggles to combat these threats on its own. Zero-day attacks, polymorphic and metamorphic malware, as well as advanced persistent threats (APTs), significantly reduce the effectiveness of traditional signature and heuristic-based systems.

On the other hand, deep learning and artificial intelligence-based security systems can detect unknown and complex attacks, offering proactive defense. They can analyze behavioral patterns in real time. However, these technologies require higher computational resources and expert knowledge, and they still have certain shortcomings against adversarial attacks. Therefore, hybrid defense models that combine traditional antivirus methods with AI-based approaches are considered a promising and

effective strategy. A hybrid approach provides both rapid defense against known threats and the ability to detect new and advanced attacks through deep learning.

Consequently, the future of cybersecurity will be based on multi-layered and integrative approaches. Organizations and individual users will create more robust, adaptive, and agile defense strategies by combining both traditional antivirus solutions and AI-based models. This approach provides comprehensive defense against cyber threats and serves as an effective tool against future, increasing cyberattacks. It minimizes defense gaps and reduces vulnerabilities.

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Phone: +994 50 209 59 68
+994 55 209 59 68
e-mail: info@aem.az

