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Digitalne inovacije u sistemima obaveštajnog odlučivanja: uloga mašinskog učenja

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Apstrakt: Savremeni obaveštajni sistemi doživljavaju duboku transformaciju pod uticajem digitalnih inovacija, pri čemu mašinsko učenje (ML) postaje instrument za unapređenje procesa odlučivanja. Brzi razvoj informacionih tehnologija omogućava prelazak sa tradicionalnih, manuelnih metoda analize ka automatizovanim i prediktivnim modelima, što omogućava bržu obradu velikih količina heterogenih podataka iz različitih izvora, uključujući IoT senzore, satelitske snimke, mrežne tokove i društvene medije. Rad pruža sistematski pregled teorijskih osnova i praktičnih primena ML u obaveštajnim sistemima, analizirajući nadzorovano, nenadzorovano i duboko učenje, njihove prednosti i ograničenja, kao i uticaj na preciznost i efikasnost donošenja odluka. Poseban akcenat stavljen je na izazove primene ML, uključujući tehničke aspekte (heterogenost i visoka dimenzionalnost podataka), bezbednosne rizike (napadi na modele, curenje poverljivih informacija) i etičke dileme (pristrasnost algoritama, transparentnost i poverenje korisnika). Pregled literature i empirijskih studija ukazuje na rastući trend integracije ML sa metodama višekriterijumske analize, hibridnih modela „human-in-the-loop“ i objašnjivih modela (XAI), čime se unapređuje kontrola rizika i interpretabilnost odluka. Budući pravci razvoja uključuju povećanu robustnost modela, adaptivnost na nove pretnje, kao i sinergiju sa drugim digitalnim tehnologijama, poput blockchain-a i kvantne analitike. Zaključuje se da mašinsko učenje predstavlja alat za unapređenje efikasnosti, tačnosti i otpornosti obaveštajnih sistema, pri čemu ljudski nadzor ostaje ključan za održivu primenu u dinamičnom digitalnom okruženju.

Ključne reči: digitalne inovacije, obaveštajni sistemi, mašinsko učenje, automatizacija, XAI

Digital Innovations in Intelligence Decision-Making Systems: The Role of Machine Learning

Abstract: Modern intelligence systems are undergoing a profound transformation driven by digital innovations, with machine learning (ML) emerging as a key tool for enhancing decision-making processes. The rapid development of information technologies enables a shift from traditional, manual analysis methods to automated and predictive models, allowing faster processing of large volumes of heterogeneous data from various sources, including IoT sensors, satellite imagery, network traffic, and social media. This paper provides a systematic review of the theoretical foundations and practical applications of ML in intelligence systems, analyzing supervised, unsupervised, and deep learning, their advantages and limitations, as well as their impact on decision-making accuracy and efficiency. Special attention is given to the challenges of ML implementation, including technical aspects (data heterogeneity and high dimensionality), security risks (model attacks, data leaks), and ethical dilemmas (algorithmic bias, transparency, and user trust). The literature and empirical studies indicate a growing trend of integrating ML with multi-criteria decision making (MCDM) methods, human-in-the-loop models, and explainable AI (XAI), enhancing risk control and decision interpretability. Future development directions include increasing model robustness, adaptability to new threats, and synergy with other digital technologies such as blockchain and quantum analytics. The study concludes that machine learning is a tool for improving the efficiency, accuracy, and resilience of intelligence systems, while human oversight remains essential for sustainable application in a dynamic digital environment.

Keywords: digital innovations, intelligence systems, machine learning, automation, XAI

1. Introduction

Modern intelligence systems are undergoing a profound transformation driven by digital innovations that redefine the methods of data collection, processing, and interpretation. The rapid development of information technologies, particularly in the fields of artificial intelligence and machine learning, has enabled a shift from traditional analytical approaches to automated, data-driven decision-making models. In this context, machine learning has become a key tool for enhancing intelligence processes, increasing the accuracy of predictions, and improving the management of complex security-related information.

The significance of this topic arises from the growing need for intelligence systems to adapt to new digital conditions, where the volume, velocity, and variety of data exceed the capacities of traditional human analysis (Zhu et al., 2023). Digital innovations, such as automated analytics systems, predictive modeling algorithms, and neural networks, have the potential to transform decision-making processes in areas including national security, cyber defense, and strategic planning (Vudugula et al., 2023).

The purpose of this manuscript is to systematically examine the role of machine learning in intelligence processes through the analysis of existing research, models, and technological trends. Emphasis is placed on identifying the benefits, limitations, and future directions of these technologies. The aim of the paper is to provide a comprehensive overview of both theoretical and practical aspects of applying machine learning in intelligent decision-making systems, while considering the impact of digital innovations on efficiency, accuracy, and information security. The structure of the paper is organized to first present the fundamental concepts of digital innovations and machine learning, then to analyze relevant literature and existing applications, and finally to summarize challenges, perspectives, and directions for future research.

2. Digital Innovations in Intelligence Systems

Digital innovations have, in recent decades, reshaped paradigms within intelligence decision-making systems (Lombardi & Vannuccini, 2021). Traditional intelligence

systems relied on manual data collection, human analysis, and decision-making through hierarchical structures. With the emergence and development of information and communication technologies (ICT), high-performance computing, the Internet of Things (IoT), and big data, the intelligence decision-making process has expanded and accelerated (Ali et al., 2024). The advent of technologies such as real-time analytics, automated multi-source data collection, and the application of machine learning algorithms has enabled a shift from reactive to proactive and predictive intelligence processes. For instance, research on enterprise digital intelligence indicates that the transformation of “digitally intelligent” enterprises involves connecting the external environment and users through data, networks, and smart technologies (Liu & Song, 2024). Bibliometric reviews of digital innovations demonstrate a growing research trend and identify dimensions such as antecedents, execution, outcomes, and levels of digital innovation (Manotti et al., 2020). In the intelligence context, this implies that technologies enabling digital transformation – software, sensors, connectivity, and algorithms – become essential for generating and utilizing information for decision making. The development of digital technologies has impacted not only the technical platform but also organizational processes and culture: intelligence agencies and systems must integrate interdisciplinary approaches, ranging from data engineers and analysts to strategic managers. Furthermore, the increased complexity and heterogeneity of data sources (e.g., satellite imagery, signals, social media, and network streams) require new models of management and analysis.

Digital transformation in intelligence systems can be conceptualized through three stages: data collection, processing/transformation, and analysis for decision-making (Han et al., 2025). Digital technologies enable automated, continuous, and large-scale data collection from diverse sources. IoT sensors, drones, satellite sensors, network logs, social media, and other digital traces present significant potential for intelligence systems. These innovations allow for much greater speed and variety in data collection compared to previous manual methods. The vast volumes of raw data require efficient methods for cleaning, integration, aggregation, and transformation into a format suitable for analysis (Dhawas et al., 2024). In this context, data management platforms and ETL (Extract, Transform, Load) processes play a crucial role. Investments in digital infrastructure allow intelligence systems to operate in real-time or near-real-time. At this level, technologies such as big data analytics, machine learning algorithms, data visualization, and decision support systems enable the transformation of data into knowledge and action. A study by Kowalski (2023) demonstrates that the combination of AI and analytics significantly improves both accuracy and decision-making speed, while also identifying barriers such as data integration, algorithmic bias, and system interoperability. In the intelligence context, this means that digital transformation facilitates better connectivity between data sources and analytical models, a shift from reactive

procedures (post-incident) to predictive and preventive ones, and greater efficiency in resource allocation and timely decision-making.

Automation in intelligence systems involves the use of software agents, algorithms, and robots to collect, filter, and analyze information with minimal or no human intervention (Heer, 2019). Automation accelerates the data collection process and reduces human error but also introduces new challenges – ensuring that automated processes correctly interpret and classify data, handling misinformation, and integrating human oversight within automated systems. Big data represents the concept and practice of working with extremely large, complex, and heterogeneous datasets that exceed the capabilities of traditional processing methods (Rao et al., 2019). In intelligence systems, big data sources include network signals, satellite data, social media data, telecommunications streams, IoT sensors, and similar sources. Analyzing such data can reveal patterns, anomalies, and trends that human analysts could not detect using traditional techniques. For example, Almanasra (2024) shows that integrating AI and big data technologies leads to significant improvements in efficiency, accuracy, and security. In this context, analytics refers to a set of techniques that allow the interpretation of collected and processed data for decision-making purposes (Sarker, 2021). Analytics can be divided into three layers: descriptive (what happened), predictive (what might happen), and prescriptive (what should be done). In intelligence systems, predictive and prescriptive analytics are particularly important because they enable threat anticipation, scenario simulation, and actionable recommendations. Digital innovations allow analytics to operate in near real-time, with automated models that continuously improve through machine learning.

Automation, big data, and analytics are not isolated phenomena – they complement each other. Automated systems collect large amounts of data, big data infrastructure enables storage and management of these data, and analytics (combined with machine learning) transforms it into actionable insights (Alaassar et al., 2025). The literature on digital innovations highlights that “data-driven operation, instant release, and swift transformation” serve as mechanisms for the rapid scaling of digital innovations (Manotti et al., 2020).

3. Machine Learning in the Context of Intelligence Decision-Making

Machine learning (ML) is a subfield of artificial intelligence that enables systems to learn from data, recognize patterns, and make predictions without explicitly programming all rules (Taye, 2023). In intelligence decision-making, ML can support the processes of selection, classification, and prediction of large volumes of heterogeneous data, which is particularly relevant for high-risk and uncertain systems. A study conducted by Salem et al. (2024) demonstrates that the application of ML algorithms can significantly enhance the rationality of decision-making in public administration and e-governance. The most important aspects include automatic extraction of meaning from data, accelerated processing, and scalability in complex systems. In intelligence systems, the theoretical foundations of ML approaches include:

- modeling input data (supervised or unsupervised) originating from diverse sensors, signals, and communications,
- constructing and training algorithms that optimize a target function (e.g., threat classification, anomaly detection, risk prediction),
- performance evaluation (accuracy, recall, precision, F-measure) and interpreting results in the context of decision-making,
- integration with decision support systems, where ML models serve as tools for generating options, alerts, or predictions for human analysts (Salem et al., 2024).

A study by Merkert et al. (2015) indicates that the usefulness of ML algorithms for decision support systems depends on the task and the stage of the decision-making process in which they are applied. Table 1 provides an overview of algorithm types. The application of different algorithm types allows intelligence decision-making systems to respond flexibly to various challenges – supervised learning for known scenarios, unsupervised learning for discovering unforeseen patterns, and deep learning for complex multimedia sources.

Table 1: Types of Algorithms (Supervised, Unsupervised, Deep Learning)

Category	Description	Examples of Application in Intelligence Decision Making
Supervised Learning	Algorithms trained on labeled data (input-output), aiming at prediction or classification.	Classification of communications as security threat or not, prediction of attack risks.
Unsupervised Learning	Algorithms that identify structure in data without pre-defined labels (e.g., clustering, dimensionality reduction).	Detection of unknown communication clusters or anomalous patterns indicating security threats.

Deep Learning	Multi-layer neural models capable of processing complex, high dimensional data (e.g., images, signals, text).	Processing satellite imagery, video materials, social network analysis for intelligence purposes.
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Source: (Naeem et al., 2023)

In intelligence systems, ML technologies provide the following contributions (Rao et al., 2024):

- Automation of the analysis of large volumes of data from diverse sources (satellite imagery, IoT sensors, telecommunication flows, social media).
- More precise identification of risks and threats through advanced scenario prediction modeling.
- Faster response due to algorithmic processing and generation of alerts in real or near-real time.
- Support for analysts through systems that suggest actions, describe scenarios, and prioritize tasks.

Salem et al. (2024) confirm that ML positively affects decision-making rationality in the public sector – the application of supervised and unsupervised learning significantly increases efficiency and speed. Furthermore, Ali et al. (2023) highlight the integration of ML with multi-criteria decision-making methods as “intelligent decision support systems”. In the intelligence context, the application of machine learning faces a number of specific challenges. One issue is the heterogeneity and high dimensionality of data, as intelligence systems collect information from diverse sources and in different formats, requiring rapid and efficient data integration. Additionally, models must be capable of detecting unknown situations, so-called zero-day threats, i.e., patterns that have not been previously identified, and not only known threats. A particular challenge is the tendency of deep models to operate as “black boxes,” which reduces transparency and interpretability, whereas auditability is critical in intelligence systems (Matthew, 2025). Ethical considerations, privacy, and user trust also play a significant role, as research shows that trust in algorithmic decisions greatly affects technology adoption (Ghasemaghaei & Kordzadeh, 2025). Finally, the integration of machine learning with human decision-making presents an additional challenge – the model and the analyst must be coordinated so that the human factor remains in the loop, as insufficient synergy can lead to misinterpretations or excessive automation.

ML represents a significant component of digital innovations in intelligence systems. Understanding its theoretical foundations, properly applying the appropriate algorithm types, and being aware of the challenges allows ML models to be used as tools in intelligence decision-making systems, but not as replacements for human analysis.

4. Review of Relevant Research

Research on the application of ML in decision-making systems has been rapidly increasing. For example, Lai et al. (2021) analyzed over 100 empirical studies on human-AI collaboration in decision-making, highlighting gaps within three dimensions – decision-making tasks, AI models, and supporting elements, along with evaluation metrics. Furthermore, Mohamed (2023) emphasizes how deep learning redefines the analytical capabilities of organizations for decision-making, pointing to the interdisciplinarity and the connection between strategic approaches and data presentation. Vourganas and Michala (2024) conclude that qualitative and quantitative challenges in data limit the full effectiveness of ML models in detection and prevention. Emerging trends include:

- A shift from isolated models to hybrid systems where ML is integrated with human decision-making.
- A focus on transparency and explainability as a response to the need for auditability (Mohseni et al., 2021).
- Increased attention to the security risks of ML systems, which directly affect their usability in intelligence domains (Paracha et al., 2024).
- Discussion on the structure and dynamics of human-machine relationships in decision-making, rather than solely on technical implementation.

Table 2: Models and Their Applications in Decision-Making Domains

Approach/Model	Application in Decision Making Domains	Specifics and Notes
ML + MCDM Integration	Analysis and ranking of options in complex decision-making systems	Combination of predictive ML models and multi-criteria decision-making (MCDM) analytical methods (Ali et al., 2023)
Human-in-the Loop Hybrid	Inclusion of the human factor in ML decision making processes	Wang et al. (2022) highlight gaps in the literature
Explainable AI (XAI) Models	Critical when decision transparency is required (e.g., intelligence systems)	Multidisciplinary review emphasizes the importance of design and evaluation of XAI systems (Mohseni et al., 2021)

Robust/Adversarial-Resistant Models	When the system is exposed to adversarial attacks (e.g., cybersecurity)	Kawamoto et al. (2023) provide a review classifying vulnerabilities
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Source: (author)

The review provided by Ali et al. (2023) reveals that ML algorithms are most frequently applied alongside multi-criteria decision-making (MCDM) methods in complex decision-making problems. Table 2 presents several models/approaches mentioned in the literature, along with their specific applications in decision-making contexts. The literature indicates that the most effective approaches in intelligence decision-making combine relevant data, tailored algorithms, human oversight, and mechanisms for assessing model risk and bias.

Although the application of ML in decision-making systems offers significant advantages, the literature highlights extensive limitations and challenges:

- Data quality and quantity are often insufficient. Reviews on ML in cybersecurity emphasize that the diversity and heterogeneity of data sources, inconsistency of features, and lack of standardized datasets limit model validity (Shaukat et al., 2020).
- Model bias and interpretability: Without adequate human oversight and understanding, ML decisions can be unreliable in critical systems. Research on XAI and human-in-the-loop approaches indicates that existing studies insufficiently address how users (analysts, decision-makers) understand and apply ML outputs (Mohseni et al., 2021).
- Security risks of ML systems: Model attacks, data theft, and manipulation of model training represent real threats, especially in intelligence systems that rely on confidential information (Blauth et al., 2022).
- Generalization and applicability in specialized domains: Many studies come from commercial or industrial domains and are difficult to directly translate to highly specialized scenarios, such as intelligence systems, where conditions, pressures, and risks differ (Perez-Cerrolaza et al., 2024).
- Ethical and regulatory barriers: Integrating ML models into systems that affect national security, strategic decision-making, or risk management must consider ethics, legislation, and accountability, which the literature often identifies as underdeveloped areas (Montasari, 2024).

While the literature provides rich insights and evidence on the effects of ML in decision making processes, its application in intelligence systems requires further adaptation and research – particularly regarding the human factor, system security, and domain-specific requirements.

5. Challenges, Innovations, and Future Directions of Machine Learning Application in Intelligence Systems

The application of machine learning (ML) in intelligence systems faces multiple layers of challenges. Technical challenges include data heterogeneity, high dimensionality, and the need for fast real-time processing. Models often require large datasets for training, while access to high-quality and reliable data is limited in intelligence contexts. Ethical challenges relate to privacy, transparency, and accountability in decision-making. Algorithmic decisions can be biased or non-explainable, potentially leading to incorrect risk assessments or inadequate operational responses (Hotko, 2024). Security challenges involve vulnerabilities of ML models to attacks, data manipulation, and leakage of sensitive information, which are critical in the intelligence sector.

Research trends indicate the development of hybrid systems in which machine learning operates in coordination with human analysts, enabling “human-in-the-loop” decision making models (Kumar et al., 2024). Further development focuses on increasing model explainability (XAI), robustness against attacks, and the ability to adapt to new, unknown threats.

The integration of ML with other technologies opens additional opportunities. Combining ML with artificial intelligence allows advanced analysis and prediction; blockchain can provide secure and transparent data records, reducing the risk of manipulation; quantum analytics potentially enables faster processing of complex and high-dimensional data, which is strategically important in intelligence decision-making.

The perspective for ML development in intelligence systems is oriented toward secure, explainable, and adaptive application, in synergy with advanced digital technologies and human oversight.

6. Conclusion

Digital innovations and the application of machine learning (ML) significantly transform intelligence decision-making systems, changing the ways information is collected, processed, and interpreted. A review of the literature and analyzed application examples show that automation, big data, and analytics, combined with ML algorithms, enable more precise threat identification, faster data processing, and enhanced decision-making in real or near-real time. Machine learning allows for scalability and adaptability of systems, while different algorithmic approaches – supervised, unsupervised, and deep learning – address various types of challenges, ranging from routine scenarios to complex, multimedia, and previously unknown threats.

At the same time, the application of ML in intelligence systems faces multi-layered challenges. Technical challenges include data heterogeneity, high dimensionality, and the need for real-time processing, while ethical and security challenges encompass transparency, algorithmic bias, privacy protection, and vulnerability to attacks. The human factor remains crucial for interpreting and evaluating ML model outputs, highlighting the need for a “human-in-the-loop” approach and the integration of explainable AI (XAI) models into intelligence processes.

A review of current research indicates that the most effective approaches combine algorithmic automation, multi-criteria decision analysis methods, human oversight, and mechanisms for controlling model risks and biases. Future development directions focus on hybrid systems, increased explainability, robustness, and adaptability of models, as well as integration with other digital technologies such as blockchain and quantum analytics, enabling safer and more efficient processing of large and heterogeneous datasets.

Machine learning represents a key component of digital innovations in intelligence systems, not as a replacement for human analysis, but as a tool to enhance the accuracy, speed, and quality of decision-making. Its effective application depends on balancing technological capabilities with human oversight, security, and ethical standards, enabling intelligence organizations to achieve sustainable efficiency and resilience in a dynamic and complex digital environment.

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