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The Use of Trained AI to Automate Decision-Making in Industrial Systems

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ABSTRACT

The article discusses issues related to the specifics of using trained artificial intelligence (AI) to automate decision-making (with an emphasis on the industrial sector). The importance of addressing the topic is predetermined by the growing demands on the efficiency and reliability of industrial systems (especially against the background of rapid digitalization, which permeates all areas of activity without exception). In the current environment, trained AI is becoming a key tool to help establish and optimize production processes, as well as reduce operating costs. At the same time, its application in the field under consideration is accompanied by several contradictions, including the implied lack of unified approaches to its integration, limited methods for assessing the quality of those decisions that are made, and insufficient attention to issues of ethical responsibility. The purpose of the study is to analyze existing developments regarding the integration of trained AI into industrial systems, systematization (based on familiarization with scientific publications) of advantages, and related limitations. The article summarizes modern achievements in the field of predictive analytics, security management methods, and the protection of AI systems from adversarial attacks. The conclusions point to the need to unify methodological approaches, increase the resilience of AI to external threats, and develop standards governing its use. The presented materials will be useful to scientists dealing with the problems of artificial intelligence, and automation, specialists in industrial safety, and heads of enterprises interested in the digitalization of production.

KEYWORDS: *automation, security, deep learning, artificial intelligence, machine learning, predictive analytics, industry, digitalization.*

INTRODUCTION

Modern industries face the challenge of processing large volumes of information flows in real-time and finding optimal solutions under conditions of uncertainty. In this context, the application of machine learning-based artificial intelligence (AI) emerges as a highly valuable tool for automating decision-making processes. Unlike traditional algorithms that rely on rigidly defined rules, AI can adapt to changing conditions by learning patterns from historical data and current events. As a result, many contemporary researchers are focusing on a comprehensive analysis of the potential integration of this tool into industrial systems, exploring implementation approaches and evaluating its impact on process efficiency.

Despite the significant potential of machine learning-based AI in automating decision-making in industrial contexts, several challenges accompany its application. These include limited data availability, risks of distortions when processing large volumes of information, and the lack of universal standards for integrating with existing management systems. Additionally, difficulties in assessing the reliability and explainability of AI-driven actions create further barriers to its broader adoption.

METHODS AND MATERIALS

The preparation of this article involved comparative analysis, systematization, synthesis, and generalization. Contemporary studies can be categorized into several primary areas.

The works of E. Carpanzano [1] and T. Hosoda [5] consider the issues of theoretical analysis of artificial intelligence methods for decision-making. The authors focus on the latest achievements applied in industrial management systems. They emphasize the importance of adaptive algorithms, which take into account the dynamics of external conditions and ensure optimal control. They also investigate the role of AI in the context of human decision-making.

Industrial applications of AI are analyzed in detail in the works of J.V. Garrel and co-authors [3], V.T. Nguyen and colleagues [7], as well as L. Petriashvili and co-authors [8]. A morphological classification of AI-based systems used in manufacturing companies is proposed; key components and implementation strategies are highlighted. Approaches are being developed to optimize the maintenance of multi-level component systems using AI tools.

The works of M.C. Horowitz, E. Lin-Greenberg [4], S.A. Humr and coauthors [6], A. Trunk and colleagues [10], and Z. Zakota [11] discuss aspects of human-AI interaction and the influence of algorithms on strategic decisions.

The literature review reveals that researchers primarily focus on developing predictive analytics models, integrating AI into safety systems, and establishing a methodological foundation for AI training. However, discrepancies are evident in the studies. For instance, there needs to be a unified approach to integrating AI into existing production processes or evaluating the quality of decisions. Issues such as standardization and the ethical responsibilities associated with automated systems still need to be explored.

RESULTS AND DISCUSSION

The essence of trainable artificial intelligence lies in its ability to analyze data, identify patterns, and apply acquired knowledge to task execution, process optimization, and decision-making. Compared to traditional algorithms that rely on strictly predefined rules and instructions, trainable AI can independently improve its models based on experience [11]. Its fundamental characteristics include:

- Data processing: Trainable AI analyzes input data—textual, numerical, visual, or auditory signals—which are the foundation for building models and making predictions.

- Self-learning capability: The system's ability to learn autonomously is a core feature. At this stage, historical data are utilized to minimize errors during task execution. Learning can take various forms (Fig. 1).

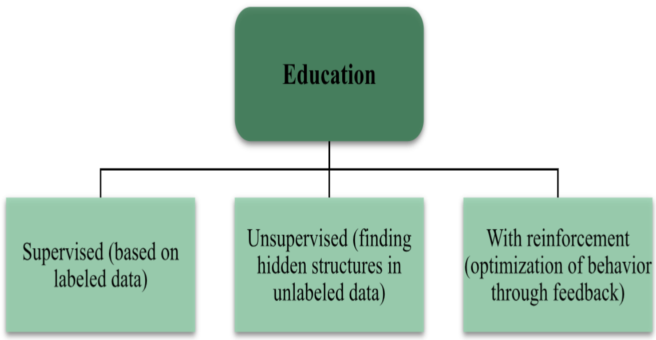

Fig. 1. AI Training Options [5, 11]

- Generalization of experience: Trainable AI establishes universal patterns that enable it to solve tasks not explicitly included in its initial algorithm. This distinguishes it from traditional systems, which are constrained by their pre-programmed functionality.

- Prediction and adaptation: AI analyzes current data, makes predictions, and bases decisions on them. As new data becomes available, the system updates its models, allowing it to adapt to changes.

Optimization tasks: AI addresses optimization challenges, including cost reduction, accuracy improvement, and increased operational speed, through mathematical models and methods such as neural networks and decision tree algorithms.

The use of trained artificial intelligence to automate decision-making in industrial systems is based on a number of key technologies.

One of the most important concepts is customizing LLM (large language models) for tasks. This is represented by adapting large-scale language models to perform highly specialized industrial tasks (e.g., data analysis, forecasting of production indicators, and process optimization).

Industrial engineering plays a significant role in automation. The approach is to create carefully thought-out queries for the model that guide its work in the right direction. Industrial tasks include generating instructions, analyzing technical documentation, preparing reports, etc.

RAG (Retrieval Augmented Generation) combines generative models and information retrieval mechanisms. This is especially important in industry, where solutions must be based on up-to-date data. This approach integrates external information sources or knowledge bases, ensuring high accuracy and relevance of AI proposals in solving complex tasks (resource management, logistics optimization).

Fine-tuning complements customization, allowing models to be adapted to specific production tasks through additional training on specialized datasets. In the industry, this includes training based on data on the specifics of equipment, production technologies, and interaction schemes in supply chains, which increases the accuracy and reliability of automated solutions.

Finally, the key place belongs to the dataset and knowledge base. To create effective automation systems, high-quality datasets reflecting the real dynamics of production processes are required, as well as carefully organized knowledge bases that provide models with access to structured information. They form the foundation for AI training and improve the accuracy of its decisions.

The operation of trainable AI relies on a set of guiding principles outlined in Table 1.

Table 1. Principles of operation of the trained AI [1, 5, 11]

Principle	Description
Data Usage	Requires a large volume of information reflecting various aspects of tasks.
Imperativeness	The training process consists of repeated attempts to improve predictions and significantly reduce errors.
Explainability	Modern AI training approaches emphasize the need for decision explainability to enhance user trust.

Ultimately, this represents a dynamic system that evolves through data analysis, achieves high levels of process automation, and improves its functionality based on accumulated experience.

The application of trainable AI in industrial systems is driven by its ability to identify optimal strategies based on information derived from complex technical systems. Such technologies significantly reduce the human factor, which is particularly critical for managing essential systems, including:

- Energy;

- Logistics;

- Mechanical engineering [3, 6].

The global AI market in industry is projected to reach $4.9 billion by 2027, with an average annual growth rate of 34.2%. AI implementation in production management systems helps automate over 40% of routine tasks, including equipment monitoring and quality control, thereby increasing overall productivity by 10–20% [2].

As noted earlier, one of the key features of AI is its ability to self-learn. In industrial contexts, this manifests in AI models analyzing sensor data, operational results, and external conditions to form recommendations or make automated decisions. For example, machine learning systems can predict equipment wear, predict optimal maintenance schedules, preventing potential failures.

The foundation of effective AI performance lies in learning algorithms. Their general characteristics have been described above, and the following discussion projects these into the industrial domain.

The supervised learning approach is utilized in tasks where input data and target values are known. This is particularly useful for scenarios such as demand forecasting or quality control. For example, neural networks are trained to detect defects on production lines using pre-labeled images.

Unsupervised learning is applied when target values are absent, requiring the system to identify patterns independently. This approach is practical for data clustering, such as client segmentation in logistics or resource allocation in manufacturing.

Reinforcement learning involves developing models that interact with the environment and receive feedback in the form of rewards or penalties. This method is particularly valuable for managing complex processes, such as optimizing transportation routes.

Implementing trainable AI systems in industry involves multi-structured architectures, including expert systems and distributed computing [8]. Deep neural networks are widely used because they can model nonlinear dependencies.

A practical example includes recurrent neural networks for predicting equipment conditions based on time series data. At the same time, convolutional networks with grid-like structures are well-suited for analyzing visual data, such as product images or surveillance videos [4].

Big Data technologies play a critical role in training AI models. The volume of data generated by industrial systems necessitates using specialized platforms (e.g., Hadoop, and Spark) that enable analysis in distributed environments.

The integration of trainable AI into decision-making processes transforms traditional management approaches. Automation accelerates decision-making among multiple options and enhances accuracy by analyzing vast amounts of information.

AI-based systems have already demonstrated high efficiency in industries such as metallurgy and chemical production. For example, machine learning-powered alloy composition forecasting improves product quality and reduces raw material costs.

Furthermore, AI systems can account for numerous interrelated factors, making them indispensable for multi-criteria optimization tasks. In the energy sector, relevant algorithms help balance loads in electrical grids, preventing failures and minimizing costs.

In conclusion, trainable artificial intelligence is crucial in transforming industrial systems, offering opportunities to enhance efficiency, reduce costs, and improve management quality. However, its integration involves significant advantages and limitations that must be considered during automation planning.

Table 2 below presents the author's perspective on systematizing features related to using trained AI in decision-making automation for industrial systems.

Table 2. Features of the use of trained AI to automate decision-making in industrial systems (compiled by the author)

Advantages	Disadvantages
AI can process large volumes of data and deliver results faster than humans, which is critical for tasks requiring prompt responses (e.g., energy system management and logistics optimization).	More accurate or better-quality data must be provided, inevitably leading to erroneous forecasts and decision-making failures.
AI learns from new data, allowing it to adjust its models and adapt to changing conditions, such as predicting equipment failures based on updated performance indicators.	Most AI models function as a "black box," making it challenging to interpret decisions, especially in critical industries.

Automation minimizes errors caused by subjective or incorrect operator actions.	AI systems' development, configuration, and maintenance require substantial financial investments, which may not pay off during the initial stages.
AI considers numerous factors simultaneously, making it indispensable for complex processes such as production planning and supply chain management.	AI integration increases the risk of cyberattacks, leading to data distortion or system failures.
Utilizing historical data enables AI to make accurate forecasts (e.g., resource consumption and product demand).	AI sometimes fails in conditions outside its training dataset or when creativity is required.

Using trained AI in industrial settings represents a breakthrough in automation, providing opportunities for analyzing complex data, forecasting events, and reducing decision-making time. The advantages of these technologies, such as their ability to process extensive data streams and adapt to changes, make AI an attractive tool in this domain.

However, the limitations—particularly the dependence on data quality and the difficulty of interpreting decisions—call for a cautious approach to implementation. For example, insufficient information may result in incorrect outputs, which is critical in industries such as chemical production and energy. Additionally, the significant investments required for development and cybersecurity hinder the widespread adoption of the technologies discussed in this article.

Cybersecurity risks associated with AI deployment also deserve attention. Attacks frequently target industrial systems, with vulnerabilities often exploited to manipulate algorithm performance.

CONCLUSIONS

The application of trained AI, both in the present and looking toward the future, offers numerous opportunities for automating decision-making in the industrial sector, enhancing productivity, reliability, and adaptability. However, the successful implementation of such solutions requires considering industry-specific features, ensuring data security, and understanding the limitations of the technology.

AI has the potential to significantly transform management processes by providing more accurate, faster, and efficient tools. Nevertheless, its adoption demands careful preparation, including collecting appropriate data and analyzing economic feasibility.

To achieve maximum efficiency, it is advisable to combine AI with human expertise. This can help address challenges related to explainability and handling unconventional situations.

In the long term, developing artificial intelligence technologies, interpretation methods, and resilience to cyber threats is expected to establish AI as a foundational element for automation in industrial systems.

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