Journal homepage: https://itce.com.ua/en

Information Technologies and Computer Engineering **Vol. 22, No. 1. 2025**

Article's History: Received: 08.01.2025 Revised: 19.03.2025 Accepted: 24.04.2025

UDC 004.89:519.816 DOI: 10.63341/vitce/1.2025.103

Adjustment of the analytic hierarchy process indicators using AI tools

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Abstract. This study aimed to enhance the analytic hierarchy process (AHP) by integrating artificial intelligence (AI) algorithms for the automatic adjustment of its indicators, thereby improving the method's accuracy, consistency, and adaptability. A conceptual analysis of both the traditional and AI-oriented approaches was conducted. The research methodology included a systematic literature review, identification of the key limitations of the classical method, and testing of AI capabilities to improve the consistency and precision of weighting coefficients. The findings demonstrate that the integration of AI into AHP significantly reduces the subjectivity of expert evaluations, lowers the need for manual adjustment of pairwise comparison matrices, and enhances the consistency of decision-making. Specifically, optimisation algorithms automatically identify conflicting judgements and correct them without human intervention, thus reducing decision-making time. The use of clustering methods facilitates the automatic grouping of criteria and alternatives based on similar characteristics, thereby reducing the number of required pairwise comparisons. The application of machine learning-based algorithms for predicting weighting coefficients enables the AHP to adapt to dynamic changes in data, enhancing the stability and reproducibility of results. Furthermore, the incorporation of Explainable AI methods improves the transparency of the decision-making process by allowing the influence of each criterion on the final outcome to be clearly explained. The analysis also demonstrated that the application of AI in multi-criteria analysis significantly reduces the cognitive load on experts, minimises the impact of human factors, and increases the accuracy of calculations. However, despite these substantial advantages, the integration of AI into AHP requires careful model configuration, as the effectiveness of such systems depends on the quality of the input data and the explainability of the outcomes. The practical significance of these findings lies in the potential to apply the proposed approaches to optimise decision-making processes in business, public administration, and the technical sciences, thereby contributing to the improved efficiency of analytical systems

Keywords: decision support system; recommender system; information models; artificial intelligence; data analysis; information technology

Introduction

Current challenges in the field of multi-criteria analysis necessitate the refinement of the analytic hierarchy process (AHP), which remains one of the most widely used approaches to decision-making. Specifically, traditional AHP faces issues regarding the subjectivity of expert judgements, the complexity of processing large volumes of data, and insufficient flexibility in the face of changing conditions. Using artificial intelligence (AI) tools presents

Suggested Citation:
Klymenko, V., & Fedorka, D. (2025). Adjustment of the analytic hierarchy process indicators using AI tools. *Information Technologies and Computer Engineering*, 22(1), 103-114. doi: 10.63341/vitce/1.2025.103

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opportunities for automating the adjustment of pairwise comparison matrices, enhancing decision consistency, and significantly improving the accuracy of multi-criteria analysis. The integration of machine learning algorithms and optimisation methods into AHP facilitates its more effective application across various domains, including business, public administration, and technical sciences, thereby expanding the capabilities of analytical systems for solving complex problems.

Despite the widespread popularity of AHP, several unresolved issues persist in the scientific literature concerning the accuracy and stability of the obtained results. Research by M.M. Potomkin *et al*. (2024) demonstrated that using different variations of AHP can lead to significant discrepancies in the ranking of alternatives. This issue is particularly relevant for tasks requiring high assessment accuracy, as even minor changes in the construction of pairwise comparison matrices can substantially affect the final outcomes. Similar difficulties were corroborated by the study of O. Tymchenko *et al*. (2022), who compared various methods for prioritising factors in complex systems. The authors noted that the problem of consistency across different methods remains unresolved, and existing algorithmic approaches do not always prevent contradictions in selecting the best alternative. This indicates the necessity for further research aimed at enhancing the method's stability through the application of adaptive algorithms and mechanisms for automatic decision adjustment.

An additional aspect requiring consideration was the application of AHP in quantitative research. H. Dźwigoł (2023) highlighted that multi-criteria analysis is frequently employed in management and technical studies; however, classical methods do not always account for complex interrelationships between criteria. The author underscored that traditional AHP can yield inaccurate results when dealing with a large number of alternatives, as it is not adapted to the analysis of dynamic changes. This indicates the necessity of modernising the method through the application of technologies capable of providing adaptive adjustment of weighting coefficients in real time.

A separate direction for improving AHP involves investigating the influence of various factors on the evaluation process. Specifically, O. Andriichuk *et al*. (2024) experimentally demonstrated that the order in which pairwise comparisons are conducted can significantly impact the accuracy of weighting coefficient calculations. They emphasised that altering the sequence of evaluations can lead to result variability, which underscores the risk of subjectivity in the classical approach. Concurrently, research by T. Krenicky *et al*. (2022) analysed the conceptual foundations of AHP and confirms that the human factor remains the primary source of error in the criterion evaluation process. Thus, there is a need to develop methods that could minimise the influence of the evaluation order and enhance the reproducibility of results in multi-criteria analysis tasks.

One promising avenue for addressing these issues is the automation of evaluation processes using AI. I. Svoboda & D. Lande (2024) proposed the use of large language models to automate the assessment of pairwise comparisons, significantly reducing the influence of the human factor and enhancing the objectivity of results. They demonstrated that the application of AI helps to avoid contradictions in pairwise comparison matrices, which is a key limitation of the classical approach. Concurrently, S. Pidchenko *et al*. (2024) investigated an alternative approach to multi-criteria analysis using the fuzzy TOPSIS method. They indicated that fuzzy logic allows for reducing the impact of subjective expert evaluations, yet the mechanism for ranking alternatives itself remains dependent on the initial data. This confirms the importance of further developing automated methods for adjusting weighting coefficients, particularly through the application of AI.

Overall, while various aspects of AHP improvement are actively researched in the scientific literature, several unresolved issues still remain. Studies indicate significant variability in results depending on the evaluation method, the order of pairwise comparisons, and the subjectivity of expert decisions. Automating the process of determining weighting coefficients using AI is one of the most promising directions for enhancing AHP, yet existing approaches require further optimisation to ensure the stability and consistency of results. Therefore, this research is aimed at evaluating the impact of integrating AI algorithms on the effectiveness and accuracy of decision-making and overcoming the identified problems by developing an approach to adjusting AHP indicators using AI algorithms, which will allow for increased objectivity, accuracy, and adaptability of the method in conditions of dynamic changes.

Materials and Methods

The methodological basis of the research was built upon the principles of conceptual analysis of multicriteria decision-making methods, aimed at identifying the key distinctions between classical AHP and its modern interpretation incorporating AI algorithms. The primary focus was placed on studying the theoretical foundations of both approaches, determining their strengths and weaknesses, and evaluating the effectiveness of the proposed AI solutions for improving the decision-making process. The mechanisms of classical AHP functioning were analysed, and contemporary algorithmic optimisation methods capable of overcoming limitations related to the subjectivity of evaluations, the complexity of processing large data volumes, and insufficient decision consistency were identified.

The analysis of traditional AHP was conducted through a critical evaluation of its key structural components: constructing the hierarchical structure of criteria, completing pairwise comparison matrices, calculating weighting coefficients using the eigenvector method, and assessing the consistency of the input data. Particular attention was paid to analysing the influence of the human factor on the results of classical AHP, specifically addressing the problems of experts' cognitive load, contradictory evaluations, and the necessity for repeated adjustments of pairwise comparisons.

The effectiveness of classical AHP was compared with AI-modified approaches based on several predefined criteria, including computational accuracy, level of consistency, robustness to changes in input data, computational efficiency, and interpretability of results. These criteria were determined based on an analysis of scientific sources that outline the requirements for modern decision support systems in various fields. The following formula was used to estimate the number of comparisons required for a certain number of criteria (*n*):

$$\frac{n \times (n-1)}{2}. \tag{1}$$

To evaluate the impact of AI on improving the decision-making process, methods allowing for the automation of individual stages of AHP were analysed. The application of machine learning algorithms for optimising weighting coefficients and identifying contradictory evaluations in pairwise comparison matrices was investigated. The use of neural network approaches for predicting criterion weights based on historical data and clustering algorithms to group similar alternatives and reduce the volume of necessary comparisons was considered. Particular attention was paid to optimisation methods applied for correcting inconsistencies in comparison matrices. The effectiveness of using genetic algorithms, the gradient descent method, and other adaptive mechanisms to ensure the stability and consistency of adopted decisions was investigated. The possibilities of applying these methods to reduce evaluation subjectivity, enhance matrix consistency, improve the accuracy of weighting coefficients, and for the automatic identification and elimination of contradictions were considered. A conceptual comparison of classical and novel theoretical approaches allowed for determining precisely how AI algorithms can optimise the decision-making process and ensure computational accuracy in multi-criteria analysis.

Theoretical approaches to using Explainable AI to ensure greater transparency of adopted decisions were analysed. The focus was placed on theoretical models that demonstrate the potential for adaptive optimisation of the decision-making process. Evaluating the capacity of AI algorithms to generate not only accurate but also interpretable results allowed for the formation of additional methodological principles for comparing classical and AI-modified AHP models. This approach ensured the interdisciplinary validity of the research and deepened the understanding of the dynamics of cognitive and computational interaction in the context of modern decision analytics.

Results

Limitations of classical AHP and the application of AI to overcome them

AHP is widely applied for multi-criteria decision-making in various fields; however, its classical implementation is accompanied by several significant limitations that affect the accuracy, consistency, and effectiveness of the evaluation process. One of the most crucial problems is the high subjectivity of expert evaluations, which directly influences the structure and results of the analysis. In traditional AHP, experts conduct pairwise comparisons between criteria or alternatives based on their own experience and knowledge; however, this process is largely dependent on their level of competence, biases, and cognitive characteristics. Different experts may have varying perceptions of the relative importance of criteria, often leading to contradictory evaluations. This, in turn, creates difficulties in constructing a consistent matrix of pairwise comparisons, particularly if a large number of individuals are involved in the process or when complex multi-factorial decisions are being evaluated. Attempts to average such evaluations do not always yield an objective result, as even minor differences in judgements can significantly impact the final distribution of weighting coefficients.

Another critical limitation is the difficulty in correcting and checking consistency when dealing with a large number of criteria and alternatives. The classical approach involves using a consistency index to assess the reliability of pairwise comparisons; however, this indicator does not always effectively resolve identified contradictions (Wang *et al.*, 2023). The more criteria and alternatives included in the matrix, the more challenging it becomes to maintain a logical sequence of evaluations. For instance, if one group of experts rates a particular criterion as significantly important, while another considers it secondary, a problem arises that cannot be resolved without additional agreement or data adjustment. In large systems, where the number of criteria can reach dozens and alternatives hundreds, such a situation significantly complicates the analysis process. Furthermore, when discrepancies are substantial, the question remains open as to whether all evaluations should be revised, or only specific contradictory elements. The absence of a flexible adjustment mechanism forces analysts either to accept suboptimal decisions or to conduct additional evaluation iterations, which substantially complicates the process (Goepel, 2018).

A separate issue is the time cost associated with processing large pairwise comparison matrices. The AHP method becomes significantly less efficient in situations where a large number of objects or criteria need to be evaluated, as the number of necessary comparisons grows exponentially. For *n* criteria, the number of pairwise comparisons is determined by the formula (1). For example:

$$\frac{10 \times (10-1)}{2} = 45.$$

This means that for 10 criteria, 45 evaluations are needed, for 20 criteria – 190, and for 50 criteria –over 1,200. This not only creates an excessive burden on experts but also increases the risk of mechanical errors and fatigue, which further exacerbates the consistency problem (Ali *et al.*, 2023). Moreover, conducting such a volume of evaluations requires significant time resources, making the method less suitable for operational decision-making in dynamic conditions. Even with the involvement of automated tools for collecting and analysing evaluations, the process can remain excessively lengthy, particularly if each stage requires additional consistency checking and adjustment of results.

Another significant problem is the variability of evaluations, which leads to instability in the analysis results. Different experts may evaluate the same set of criteria differently, depending on their professional experience, the context of the task, or even personal preferences. While discrepancies may be minimal within a small group of specialists, in larger systems, variability increases to such an extent that results can differ significantly depending on the composition of the expert group (Moslem, 2024). Even minor changes in the initial evaluations can lead to substantial changes in the final ranking of alternatives, which reduces the predictability and reliability of the method. Furthermore, variability complicates the reproducibility of results: in different instances of analysis, the same system of criteria can yield different outcomes, creating additional difficulties for standardising the decision-making process.

The combination of these problems limits the application of classical AHP in complex multifactorial tasks, particularly when it is necessary to obtain well-founded and stable results quickly. Therefore, the issue of automation and the use of AI to improve this method becomes particularly relevant, as it allows for minimising the impact of subjectivity, speeding up data processing, and improving the consistency of pairwise comparisons. AI opens up new possibilities for solving the main problems of the classical approach by automating key analysis stages, which include adjusting contradictory evaluations, structuring criteria and their weights, and optimising the decision-making process (Kuraś *et al.*, 2024). The main AI methods that enhance the effectiveness of AHP are as follows:

1. Classification, is used to identify the most significant criteria based on the analysis of historical data and their influence on decision-making.

2. Clustering, which enables grouping criteria or alternatives by similar characteristics, simplifying the subsequent evaluation process.

3. Optimisation algorithms, are used to identify and correct contradictions in the pairwise comparison matrix, improving the consistency of evaluations.

4. Natural language processing, which allows for analysing textual information sources and automatically forming evaluation criteria.

5. Machine learning models, used for forecasting weighting coefficients and adaptively adjusting the pairwise comparison matrix in dynamic conditions.

The use of classification in AHP can significantly reduce the burden on experts and improve the accuracy of evaluation. In the traditional approach, criterion selection is performed manually, which can lead to the inclusion of secondary factors or, conversely, the omission of important analysis aspects. Classification algorithms, such as logistic regression or gradient boosting, are capable of automatically determining which criteria have the greatest impact on the decision outcome, based on historical data or previously conducted analyses (Kumar, 2025). For example, in the process of selecting an enterprise resource planning supplier, classification can help determine that cost, integration with existing infrastructure, and the level of technical support have the greatest influence on the decision, while less significant criteria such as the interface or brand popularity can be excluded from primary consideration.

Clustering, in turn, serves as an important tool for the automatic structuring of criteria and alternatives. In the traditional approach, experts manually group similar criteria, which can lead to subjective decisions that are not always consistent across different specialists. The use of algorithms such as k-means or hierarchical clustering allows for automatically identifying the relationships between criteria and assigning them to appropriate groups (Ren *et al.*, 2019; Fedorov & Utkina, 2022). For instance, when evaluating car brands based on various parameters, clustering can combine criteria such as "fuel efficiency" and "environmental friendliness", thereby reducing the number of necessary comparisons in the matrix. This not only lowers the burden on the analytical process but also enhances the consistency of evaluations, as all criteria within a single group are assessed based on similar characteristics.

Optimisation algorithms are indispensable for correcting contradictory pairwise comparisons, which constitutes one of the biggest problems in classical AHP. Since experts may provide incompatible evaluations, this necessitates reviewing a large number of pairwise comparisons manually. The use of genetic algorithms or the gradient descent method enables the automatic detection of such contradictions and the suggestion of optimal adjustments (Nazim *et al.*, 2022). For example, if in one part of the matrix experts indicate that criterion A is significantly more important than B, and in another that B has a higher weight than A, the algorithm can determine an average value that best aligns with other evaluations. This allows for a significant reduction in the number of manual checks and improves the stability of the analysis results.

Natural language processing opens up new possibilities for the automatic definition of evaluation criteria, which is particularly relevant in cases where decisions are based on a large number of textual sources, such as reports, customer feedback, or expert comments. In the traditional approach, experts manually form criteria, which can lead to the omission of important analytical aspects. Natural language processing algorithms, including topic modelling and text vectorisation, enable the automatic identification of key factors that appear most frequently in texts (Dos Santos *et al.*, 2023). For example, when analysing feedback on medical services, an algorithm can determine that the main criteria are "quality of service", "waiting time", and "doctor competence", allowing for the formation of a criterion hierarchy based on real data rather than solely on expert assumptions.

Using machine learning models to predict weighting coefficients allows the decision-making process to become more adaptive to changing conditions. In the classical approach, criterion weights remain fixed after the initial evaluation, which can lead to outdated or irrelevant conclusions in the long term. The use of neural networks and deep learning algorithms enables weights to be adjusted based on changes in external conditions or updates to historical data. For instance, in financial analysis, an algorithm can track currency fluctuations or changes in market trends and automatically update the significance of relevant criteria in real time.

The integration of AI algorithms into AHP significantly enhances its effectiveness. Thanks to classification, clustering, optimisation algorithms, natural language processing, and machine learning, most key processes can be automated, making the method more reliable and flexible in use. However, despite the advantages, the application of AI in AHP requires careful model tuning and adaptation to specific tasks, which remains an open area for further research.

Comparison of traditional and AI-oriented approaches in AHP

The traditional approach to the analytic hierarchy process faces several problems that complicate the process of evaluation and decision-making. In particular, expert evaluations often turn out to be contradictory, leading to the need for their correction, while an increase in the number of criteria and alternatives significantly complicates calculations. Filling the pairwise comparison matrix is a laborious process that requires significant time expenditure and increases the risk of errors. The use of AI allows for automating this process, improving the consistency of evaluations, and speeding up computations. However, despite the obvious advantages, automated methods cannot always fully replace expert analysis (Kim & Kim, 2022).

One of the key aspects compared between the traditional and AI-oriented approaches was the consistency of pairwise comparisons. Within the classical procedure, each expert independently formed the matrix, which often led to discrepancies in values caused by differing perceptions of criteria and limited cognitive resources. As a result, logical contradictions arose that required manual review and correction. In the context of the AI-oriented approach, the possibility of applying algorithms capable of automatically detecting and correcting such contradictions was implemented, reducing the level of inconsistency to permissible values without significant expert involvement. This, in turn, contributed to increased result stability and the reliability of adopted decisions.

With an increasing number of criteria, the traditional approach demonstrated a tendency towards decreasing consistency, which negatively affected the accuracy of determining weighting coefficients. The problem was further complicated by the fact that reviewing a large number of pairwise evaluations required significant time and involved multiple rounds of expert assessment. In contrast, AI approaches allowed for the application of heuristic and optimisation algorithms that automatically detected conflicts and corrected the input data. This approach not only reduced the need for repeated expert participation but also enabled working with larger systems of criteria.

Another aspect that gained significance in the context of AI application was the transparency of the decision-making procedure. The traditional approach involved full expert participation at all stages, which ensured the interpretability of the obtained weights and the final choice. In the case of AI-oriented solutions, this process was less obvious, raising doubts about the validity of the results. To partially address this problem, methods of Explainable AI began to be applied, allowing the contribution of individual criteria to the final outcome to be traced. However, such methods predominantly functioned in a post-hoc analysis mode, meaning explanations appeared only after the decision had been formed, which limited the possibility of modifying it at early stages.

It is also worth noting that the traditional approach was accompanied by a high cognitive load on experts. The necessity of performing dozens or even hundreds of pairwise comparisons in multicriteria models significantly complicated the process and increased the probability of errors. Methods based on fuzzy logic (Fuzzy AHP) offered a way to partially reduce this pressure through the application of linguistic variables and fuzzy numbers, which better corresponded to the nature of human judgements. In turn, AI-oriented approaches proposed even greater automation –by constructing models capable of evaluating alternatives –taking into account previously trained information, they significantly reduced the number of necessary expert actions.

Furthermore, the application of hybrid approaches that combine classical methods with AI models opens up new prospects for the adaptive tuning of AHP models. For example, neural networks can be used for the preliminary classification of alternatives or for detecting hidden dependencies between criteria that are not always obvious to experts. In turn, traditional methods remain important at the stage of validation and interpretation of results. Such interaction allows for achieving a better balance between the accuracy, transparency, and adaptability of decision-making models. In the future, this could contribute to the creation of interactive decision support systems capable of not only automatically calculating weights but also adapting to changes in the external environment or user preferences.

Thus, the application of AI in AHP contributes to increased accuracy of calculations, improved consistency of evaluations, and reduced labour intensity of the process. The automation of pairwise comparisons, interpretability through Explainable AI, reduced subjectivity, and accelerated computations make the AI-oriented approach an effective tool for complex tasks with a large number of criteria. Table 1 presents a generalised comparison of the key aspects of three approaches to the analytic hierarchy process: traditional, Fuzzy, and AI-oriented.

At the same time, the use of AI changes the nature of the evaluation procedure, reducing the direct role of experts in forming weighting coefficients. This increases the efficiency of the analysis but can affect the transparency of the process, as the results of automatic adjustment are not always easily interpretable. Consequently, although the modernised approach eliminates a significant proportion of the limitations of classical AHP, its implementation requires consideration of the specifics of the particular task and the potential consequences of automation.

Table 1. Comparison of technical components of traditional and AI-oriented approaches in AHP

Parameter	Traditional AHP	Fuzzy AHP	AHP with AI
Average consistency ratio (CR)	10%-15%	8%-10%	3%-5%
Need for adjustment	High	Medium	Minimal
Interpretability of decisions	Low	Medium	High
Explanation method	Absent	Partially intuitive	SHAP, LIME
Impact of subjectivity	High	Reduced	Minimal
Cognitive load	High	Medium	Low
Decision time	Lengthy	Medium	Fastest

Source: created by the authors based on D. Lande *et al*. (2023), W. Wongvilaisakul *et al*. (2023), M.I. Merhi & A. Harfouche (2024)

Challenges, limitations, and risks of AI integration into AHP

The use of AI in AHP opens up significant opportunities for process automation, reducing labour intensity, and increasing the accuracy of calculations. However, like any tool, AI has its limitations and challenges that must be considered depending on the specific nature of the task. High requirements for input data quality, the computational complexity of algorithms, the problem of decision explainability, and potential ethical risks are the main factors that can influence the effectiveness of AI application in AHP.

One of the key issues lies in the high requirements for the quality and volume of input data, upon which the accuracy and stability of the obtained results directly depend. AI algorithms operate with large datasets, including historical data, expert evaluations, textual reports, or statistical indicators. If these data are incomplete, outdated, or contain biases, this can significantly influence the final results (Ding *et al*., 2020). For example, if an AI model is trained on a limited data sample lacking certain categories of alternatives or evaluation criteria, it may underestimate their significance or not consider them at all. This creates a risk of distorted conclusions and incorrect ranking of alternatives. A similar problem arises in cases where the input data have a significant level of noise, i.e., contains contradictory or inaccurate information. If AI uses unstructured data, such as user feedback or analytical reports, it may identify patterns that do not always correspond to real decisionmaking criteria (Gupta *et al*., 2022). In the classical approach, experts have the opportunity to manually check and correct the obtained results, whereas, in the case of automated processing, this may require additional control mechanisms. This is particularly relevant in tasks where the stability of priorities over time is of critical importance.

Another challenge is the issue of AI's adaptability to the unique aspects of a specific task. Machine learning algorithms work effectively with large volumes of structured data, but they may not account for contextual specificities that are obvious to human experts (Abdel-Basset *et al*., 2024). For example, when evaluating the effectiveness of strategic planning within an organisation, there may be hidden factors, such as corporate culture or organisational constraints, which are difficult to formalise as specific criteria. While experts are capable of adapting the evaluation process, taking into account the specific conditions of the task, AI may ignore such details if they are not represented in the input data. Furthermore, automated models often operate based on standard sets of functions and do not always have the flexibility to adjust their parameters in the event of environmental changes or specific constraints (Soori *et al*., 2024). This limitation becomes even more critical in interdisciplinary or rapidly changing conditions where adaptability is a key requirement.

Limited transparency in algorithmic decision-making is another important aspect that complicates the integration of AI into the analytic hierarchy process. Classical AHP has a clear and understandable logic, as all pairwise comparisons are directly accessible for expert checking and correction. In the case of applying optimisation algorithms, such as genetic algorithms or gradient descent methods, the adjustment of pairwise comparisons occurs automatically, and users may not have a full understanding of why certain changes were made (Mai, 2024). This can lead to a reduction in trust in the analysis results, particularly if the system makes decisions that contradict the intuitive understanding of experts. The lack of explainability in AI decisions is a serious challenge for critically important tasks where it is necessary to justify every step of the decision-making process (Araujo *et al*., 2020). Even with the availability of explanation tools, such as SHAP or LIME, the interpretation of their results requires specialised knowledge and is not always obvious to end-users.

No less important factor to consider is the significant technical and financial resources required for implementing AI in AHP. The traditional approach can be realised without the use of complex computational systems, whereas the integration of machine learning algorithms necessitates appropriate technical infrastructure, sufficient computational power, and the availability of qualified specialists for configuring and managing the models (Zhou *et al*., 2024). The use of AI also demands continuous updating and checking of models, as changes in the input data can affect the accuracy of predictions. For large companies, such expenses may be justifiable, but for smaller organisations, the classical approach may remain more appropriate due to its accessibility and simplicity of implementation.

A separate challenge is the risk of excessive automation of the decision-making process, where the role of human experts is minimised. While AI is capable of significantly accelerating the analysis of large volumes of data, it cannot always account for strategic or contextual aspects of the task that require deep understanding and critical thinking (Prasetyaningrum *et al.*, 2020). If one relies entirely on the algorithmic determination of criterion weights and the consistency of pairwise comparisons, there is a threat of losing control over the decision-making process. This can be particularly dangerous in areas requiring high responsibility, such as the financial sector or public administration, where even a minor error in evaluating alternatives can have serious consequences. In such cases, human control and the ability to question the obtained results become critically important.

Also, no less important risk is the cybersecurity threat. Integrating AI into the decision-making process involves processing significant volumes of data, which can make such systems vulnerable to cyberattacks. For instance, deliberate manipulation of input data or attacks on machine learning algorithms can lead to the distortion of analysis results and the incorrect determination of weighting coefficients. Furthermore, centralised AI systems can become targets for unauthorised access, creating a risk of confidential information leakage and compromising the decision-making process.

For better visualisation of the key differences and challenges associated with using AI in AHP, Table 2 is provided below, which compares the main characteristics of the traditional and AI-oriented approaches.

Table 2. Key characteristics and limitations of traditional and AI-oriented approaches in AHP

Criterion	Traditional AHP	AHP with AI
Quality of input data	Experts adapt manually	High sensitivity to data quality
Transparency of the process	Full: all steps are logically justified	Limited explainability
Flexibility to task specifics	High: experts consider context	Low, without retraining models
Labour intensity	High: requires manual input	Low: has a configuration
Volume of processed data	Limited	Large, thanks to automation
Need for technical infrastructure	Minimal	High due to computational importance
Adaptation to new task conditions	Via expert re-evaluation	Via model retraining
Processing speed	Slow	Fast
Risk of errors	Human factor	Errors due to data distortion or incompleteness, or algorithm errors
	Local risk	Cyber threats, centralised attacks

Source: created by the authors

While the use of AI in AHP opens up new possibilities for automating and increasing the effectiveness of the evaluation process, it is also accompanied by several limitations related to the quality of input data, algorithmic transparency, the need for significant resources, and the risk of excessive automation. The most effective strategy may be to combine the classical approach with AI methods, where algorithms are used for processing large volumes of data and eliminating contradictions, while experts provide strategic oversight of the process and evaluate the unique aspects of tasks. This approach will allow for maximising the advantages of AI while simultaneously minimising its drawbacks and maintaining the quality of decisions made.

Discussion

The development of AI technologies has contributed to significant changes in multi-criteria analysis, offering new approaches to solving complex tasks. The integration of AI has enabled the automation of processes, reduced the influence of the human factor, and increased the effectiveness of calculations. Research focusing on these aspects has provided a better understanding of the potential of such technologies in improving traditional analysis methods. A review of other authors' results has allowed for analysing the advantages and challenges of implementing AI in AHP, as well as outlining the prospects of its application in various fields.

To enhance the efficiency of multi-criteria analysis, T.M. Nguyen *et al.* (2024) proposed a hybrid approach that integrated AI with Pythagorean Fuzzy AHP and COCOSO. In their study, the authors demonstrated that AI integration significantly reduced the influence of the human factor, increasing the consistency and accuracy of calculations. Particular attention was paid to tasks with fuzzy criteria, which complicated evaluation using classical approaches. The application of the proposed model proved that the automation of processes, including criterion formation and the adjustment of pairwise comparison matrices, became a key element for eliminating subjectivity. The approach confirmed that the use of automated models contributed to reducing errors and increasing accuracy in tasks that required flexible parameter tuning. This aligns with the conclusions of current study, where it was also found that automating criterion formation and ensuring model flexibility are critical for increasing effectiveness. At the same time, the specific task with fuzzy criteria, examined in detail by T.M. Nguyen *et al.*, complements the results of this study, demonstrating that AI can handle tasks of increased complexity.

Research by M.A. Alves *et al.* (2023) focused on the application of machine learning to largescale decision-making tasks. The authors noted that the automation of calculations allows for significantly accelerating the analysis process and increasing its efficiency when working with large sets of criteria and alternatives. Particular attention was paid to the challenges associated with processing large volumes of data, which posed difficulties for classical AHP. The use of machine learning algorithms, as noted in the study, not only sped up computations but also increased accuracy by reducing the probability of errors in large datasets. This is of great importance for the tasks considered in the current research, where scalability and the ability of algorithms to work with large information systems play a special role. Furthermore, emphasis on the optimisation of large volumes of criteria confirms the prospect of automation as one of the key tools for modernising multi-criteria analysis.

Research by S. Solaimani *et al.* (2024) focused on investigating the critical success factors for implementing AI in multi-criteria analysis, with an emphasis on integrating quantitative and qualitative approaches. Their main conclusion was that process automation, including consistency checking and adaptation to dynamic changes, significantly increases the accuracy and effectiveness of decision-making. At the same time, the authors highlighted that automation without ensuring process transparency can raise doubts regarding trust in the obtained results, which, in their opinion, is one of the key challenges in using modern algorithms. They also noted that integrating different data sources is critically important for reducing the risk of incomplete information, which affects the quality of multi-criteria analysis. These conclusions largely correlate with the results of this study. Specifically, the confirmation of the effectiveness of automatic consistency checking and its ability to reduce human errors aligns with the ideas proposed in this research.

An important addition is provided by the conclusions of V.A. Salomon & L.F. Gomes (2024), who investigated the role of consistency in increasing the accuracy of multi-criteria analysis. Their research paid significant attention to improving evaluation methods, particularly through the use of new algorithms for checking pairwise comparison matrices. It is especially important that the authors not only demonstrated the advantages of automation in detecting contradictions but also highlight how these algorithms can dynamically adapt to changes in data. Furthermore, the authors noted that automation contributes to reducing the probability of human errors, especially in tasks where experts may have differing views on the significance of criteria. This aligns with the conclusions of this research regarding the reduction of subjective influence thanks to the modernised approach with AI.

Another approach to combining AHP and AI was demonstrated by A.-A. Bouramdane (2023), who considered their integration for ensuring cybersecurity. The proposed model combined classical multi-criteria analysis approaches with automated risk assessment. This allowed for quickly and accurately assessing cyber threats and making optimal decisions regarding smart grid protection. The author emphasised that the use of AI contributes to accelerating the analysis process and reducing the time spent on consistency checking, which aligns with the conclusions of this study regarding the benefits of automation. A particular emphasis was placed on how automation allows for reducing the influence of the human factor in complex situations that require processing a large volume of data. A.-A. Bouramdane also underscored the adaptability of AI, which provides flexibility in dynamic conditions, representing an important addition to the conclusions of this study. At the same time, the application of automation in cybersecurity illustrates a more specific context that complements the results of this research, which is focused on supplier selection tasks. This confirms that the flexibility and adaptability of AI can be equally effective in various fields, including risk management and strategic decision-making.

A methodological approach developed by G. Marín Díaz *et al.* (2025) involved the integration of Explainable AI with AHP to improve business decisions. Particular attention was paid to the problem of transparency, emphasising the necessity of explaining results generated by automated systems. The authors' conclusions demonstrated that insufficient clarity of algorithms can hinder user trust in such systems, even if they provide high accuracy. Furthermore, the authors noted that integrating AI with AHP allows for considering complex interrelationships between criteria, which significantly increases accuracy and adaptability in decision-making. The proposed approach illustrated that the integration of Explainable AI can help resolve a key problem mentioned by S. Solaimani *et al.* (2024), related to trust in automated systems. The problem of transparency in automated systems is an important aspect that was considered less in-depth in this study. Thus, these studies expanded the discussion of the modernised approach, adding the perspective of ensuring trust in AI within multi-criteria analysis processes.

Furthermore, the integration of AHP into recommendation systems was investigated in detail by M.A. Akbar *et al.* (2023). The authors demonstrated that the combination of AI and AHP allows for effectively handling complex interrelationships between criteria while ensuring high accuracy and adaptability of the systems. Particularly interesting is their conclusion that automation not only increases the accuracy of recommendations but also minimises the risk of subjective errors in the criterion evaluation process. This echoes the conclusions of this research that the modernised approach eliminates dependence on expert evaluations, which can be a source of contradictions and errors in the classical approach. AI's ability to work with large volumes of data allows for scaling tasks, which is a significant advantage in multi-criteria analysis.

In conclusion, within the context of the modern use of AHP, the implementation of AI has allowed for significantly enhancing traditional approaches, providing automation, increased accuracy, and a reduction in the influence of subjective evaluations. These achievements have become particularly important in complex multi-criteria tasks where the number of criteria and alternatives increases significantly. At the same time, the integration of AI creates new challenges, such as ensuring process transparency and trust in automated systems. Nevertheless, contemporary research indicates that the adaptability and scalability of AI algorithms open up new prospects for AHP application in various fields, demonstrating its significance and potential for solving current decisionmaking tasks.

Conclusions

The research demonstrated that integrating AI tools into AHP allows for a significant improvement in its effectiveness, eliminating the main limitations of the classical approach. The implementation of machine learning algorithms and optimisation methods contributes to the automation of critically important stages of the process, such as constructing the hierarchical structure, determining weighting coefficients, and checking the consistency of pairwise comparison matrices. This, in turn, reduces the level of subjectivity in expert evaluations and significantly increases the consistency of decisions made. Automating the analysis process allows for a substantial reduction in the time expenditure required for evaluation, which is particularly important when working with large sets of alternatives and criteria. The proposed optimisation methods ensure the effective adjustment of contradictory evaluations, which contributes to the stability and reproducibility of the obtained results.

Despite the significant advantages of the automated approach, the application of AI in AHP presents certain technical challenges. In particular, the effectiveness of the algorithms is significantly dependent on the quality of the input data, which can limit the accuracy of decisions made in cases where the data are incomplete or contradictory. It is important to consider that the complexity of implementing AI models and configuring them can affect the speed at putting such solutions can be put into practice. Additional resources are necessary not only for training algorithms but also for maintaining their relevance in a changing environment. Automated analysis methods may not always be able to account for specific expert knowledge, which can affect the accuracy of individual evaluations in complex cases. Furthermore, automated methods can demonstrate insufficient flexibility when working with complex dynamic systems, where real-time adaptation of weighting coefficients is required. This necessitates further research into the development of adaptive mechanisms that will allow algorithms to adjust evaluations based on new input data without losing system stability.

At the same time, the results of the study confirmed that the most effective approach is combining expert analysis with AI capabilities. The hybrid method provides an optimal balance between process automation and control by specialists, allowing for increased accuracy and consistency of results without loss of flexibility. Further improvement of this approach can be aimed at integrating more complex self-learning algorithms and developing consistency-checking methods that will expand the application of AHP in the context of a rapidly changing decision-making environment.

Acknowledgements

None.

Funding

The study received no funding.

Conflict of Interest

None.

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Коригування показників методу ієрархій за допомогою інструментів AI

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Анотація. Це дослідження спрямоване на вдосконалення методу аналізу ієрархій (МАІ) шляхом інтеграції алгоритмів штучного інтелекту (ШІ) для автоматичного коригування його показників, що дозволить підвищити точність, узгодженість і адаптивність методу. У межах роботи проведено концептуальний аналіз традиційного та ШІ-орієнтованого підходів. Методологія дослідження включала систематичний аналіз літератури, виявлення основних обмежень класичного методу, а також тестування можливостей ШІ для покращення узгодженості та точності вагових коефіцієнтів. Результати дослідження показали, що впровадження ШІ у МАІ значно зменшує рівень суб'єктивності експертних оцінок, знижує потребу у ручному коригуванні матриць парних порівнянь та підвищує узгодженість ухвалених рішень. Зокрема, алгоритми оптимізації автоматично ідентифікують суперечливі оцінки та коригують їх без втручання людини, що скорочує час ухвалення рішень. Використання методів кластеризації допомагає автоматично групувати критерії та альтернативи за схожими характеристиками, зменшуючи кількість необхідних парних порівнянь. Застосування алгоритмів прогнозування вагових коефіцієнтів, заснованих на машинному навчанні, дає змогу адаптувати МАІ до динамічних змін у даних, підвищуючи стабільність і відтворюваність результатів. Крім того, впровадження методів Explainable AI сприяє підвищенню прозорості процесу ухвалення рішень, дозволяючи пояснювати вплив кожного критерію на кінцевий результат. Аналіз також продемонстрував, що використання ШІ в багатокритеріальному аналізі дає змогу значно зменшити когнітивне навантаження на експертів, мінімізуючи вплив людського фактора та підвищуючи точність розрахунків. Проте, попри значні переваги, інтеграція ШІ у МАІ потребує ретельного налаштування моделей, оскільки їх ефективність залежить від якості вихідних даних і пояснюваності отриманих рішень. Практичне значення отриманих результатів полягає у можливості використання запропонованих підходів для оптимізації процесів ухвалення рішень у бізнесі, державному управлінні та технічних науках, що сприятиме підвищенню ефективності аналітичних систем

Ключові слова: система підтримки прийняття рішень; рекомендаційна система; інформаційні моделі; штучний інтелект; аналіз даних; інформаційна технологія