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USING EXPLAINABLE AI (XAI) ALGORITHMS TO INTERPRET THE RESULTS OF ANALYTICAL MODELS IN MANAGEMENT DECISION-MAKING

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Abstract
This article discusses the application of Explainable methods. Artificial Intelligence (XAI) for interpreting the results of analytical models in the context of management decisions. This paper analyzes modern approaches to explainable AI, including interpretable models (ante-hoc) and post-hoc methods for " black -box" machine learning, such as LIME, SHAP, and visualization techniques. Recommendations for integrating XAI into management practice are presented. This paper is intended for researchers and practitioners interested in improving the effectiveness and validity of data-driven decisions.

Keywords: Explainable AI, XAI, model interpretability, post-hoc explanations, LIME, SHAP, management decisions, data-driven decision making, algorithmic transparency, trust in AI, business analytics.

Introduction

With the development of machine learning (ML) and artificial intelligence (AI), data analysis methods are becoming key tools for supporting management and business decisions: demand forecasting, risk assessment, credit scoring, process optimization, customer segmentation, etc. However, many of today's powerful models (gradient boosting, ensembles, neural networks, etc.) exhibit "black box" properties: they produce good predictions, but the internal structure and logic of decision-making are often incomprehensible to humans. This opacity limits their applicability in situations requiring decision justification, accountability,

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compliance with internal regulations, or trust from managers, clients, and regulators.

It was to overcome this problem that the Explainable direction was created. Artificial XAI is a set of concepts, methods, and practices designed to make the output of AI/ML models " explainable" to humans: to understand which features (factors) influenced the prediction, how important they are, how the model responds to changes in input data, and, if possible, what algorithmic path led to the result [1].

In recent years, attention to XAI has increased significantly. Research has shown that XAI is considered "the key to trust, accountability, and transparency" when applying AI in important areas, such as healthcare, finance, law, business analytics, and others. In a business context, XAI is positioned as a way to enhance trust in automated decisions, facilitate the interpretation of models by managers, and ensure compliance with internal and external transparency and accountability requirements [2].

However, despite the popularity and wide range of proposed methods, significant challenges and limitations remain. Existing XAI methods vary in their approaches: some create interpretable "inherently transparent" models, others provide post-hoc explanations for "black boxes," and others provide global explanations (the behavior of the model as a whole), while others provide local explanations (the solution for a specific object) [3]. Moreover, as shown in In meta -studies, there are very few standardized metrics for assessing the quality of explanations: many studies are limited to subjective or anecdotal examples, and quantitative verification and assessment of the usefulness of explanations for end users (managers, analysts) are still rare [4].

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Formalization of Local and Global XAI Explanations

A local explanation aims to interpret the prediction of a model for a specific instance x_i. In general, the model prediction can be represented as an additive decomposition of feature contributions:

$$f(x_i) = \phi_0 + \sum_{j=1}^{p} \phi_j(x_i),$$

where
ϕ_0 – baseline model value (average prediction),
$\phi_j(x_i)$ – contribution of the j-th feature to the prediction for instance x_i,
p – number of features.

This representation is used in SHAP-based methods and allows a quantitative assessment of the influence of each feature on a specific model decision.

Global explanations describe the behavior of the model over the entire dataset. Global feature importance can be obtained by aggregating local contributions:

$$I_j = \frac{1}{N} \sum_{i=1}^{N} |\phi_j(x_i)|,$$

where
N – number of instances in the dataset.

This measure reflects the average contribution of a feature to model predictions and is used to analyze the overall decision structure.

Formula 1. Additive decomposition of a model prediction

Therefore, there is a significant need for empirical research that: systematizes and classifies XAI methods as applied to business and management scenarios, analyzes which methods are suitable for decision-making tasks at the management level, tests the extent to which model explanations are perceived and useful for managers and stakeholders, and identifies trade-offs between model accuracy, complexity, and interpretability.

The purpose of this article is to summarize the concept of XAI, present a taxonomy of key methods, analyze their applicability and limitations in the context of management decision-making, and offer recommendations for the implementation of XAI approaches in business analytics, taking into account the needs of managers, requirements for transparency and accountability.

Taxonomy and classification of XAI methods. Explainable area Artificial In recent years, the field of artificial intelligence (XAI) has generated numerous methods for improving the interpretability and transparency of machine learning

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(ML)/AI models. However, the diversity of approaches often makes it difficult to select the appropriate method for a specific task. Therefore, a systematic overview and a clear taxonomy are essential.

One of the most complete and recognized taxonomies is presented in the work “A comprehensive taxonomy for explainable artificial intelligence: a systematic survey of surveys on methods and concepts". This study analyzed more than 50 reviews and systematized the main concepts, approaches and characteristics of XAI methods [5]. Also, the review “Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI» distinguishes two major categories of methods: inherently interpretable (initially “transparent”) models and post - hoc methods applicable to “black boxes” [6]. Below are the main categories and the logic behind their distinction according to key criteria frequently used in the literature.

XAI methods differ along a number of axes:

1. Interpretability initially (intrinsic / inherently interpretable) vs post- hoc, that is, either we choose models that are inherently transparent, or we apply explanatory mechanisms after training a “black” model.
2. Local vs. global explanations . Local explanations provide an explanation for a specific prediction; global explanations provide insight into the model's behavior across the entire dataset.
3. Model - agnostic vs. model - specific. Model- agnostic methods can be applied to any model; model-specific methods are developed for a specific class of models (e.g., neural networks, decision trees, etc.).
4. Explanation presentation format: feature weights/feature importance, visualization (graphs, heat maps, activation visualization), counterfactual explanations, rules/logical forms, surrogate models, etc.

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Formal Taxonomy of Explainable AI Methods

The set of Explainable AI methods can be represented as a classification along four independent axes:

$$XAI = \langle T, S, M, F \rangle,$$

where

$T \in \{intrinsic, post\text{-}hoc\}$ – interpretability type,

$S \in \{local, global\}$ – explanation scope,

$M \in \{model\text{-}agnostic, model\text{-}specific\}$ – model dependency,

F – explanation format.

Each XAI method can be formally described as an element of this space. For example, the SHAP method belongs to the class:

$$SHAP \in \{post\text{-}hoc, local/global, model\text{-}agnostic, feature\ attribution\}.$$

This representation enables systematic comparison of XAI methods and supports the selection of appropriate techniques depending on task requirements and the managerial decision-making context.

Formula 2. Formal representation of the XAI taxonomy

Based on these axes, the XAI methods can be structured into Table 1.

Table 1 - Basic approaches and methods of XAI

Category / Method	**Type (intrinsic / post -hoc)**	**Locally / Globally / About**	**Model -independent / -specific**	**Explanation Format/Features**
Simple "transparent" models (linear regression, logistic regression, decision trees, rule- -based models, GAM, etc.)	intrinsic	Globally (and locally - by rules/trees)	model -specific (or model class specific)	Clear, understandable rules, coefficients, decision tree - easy to interpret manually
LIME (Local Interpretable Model -agnostic Explanations)	post -hoc	Locally	independent model-	Approximation of a complex model by a locally simple interpretable one (e.g. linear), explanation "for one case"
SHAP (Shapley Additive exPlanations)	post -hoc	Both locally and globally (local SHAPs + aggregated global explanations)	the model -is independent (but there are optimized versions for some classes)	Evaluation of the contribution of each feature in terms of Shapley contributions (game theory), the ability to visualize the importance of features, stability, compatible with tabular , text , image , etc.
Visualization methods for neural networks (e.g. saliency -maps , Grad -CAM, Integrated Gradients , etc.)	post -hoc	Usually locally (for a specific example)	model- -specific (for neural networks)	Visual maps showing which parts of the input data (images, text, etc.) influence the decision - useful for visual/ multimodal tasks
Counterfactual explanations (-if -- then scenarios)	post -hoc / hybrid methods	Locally / globally (depending on implementation)	more often the model -is independent (or with easy adaptation)	Explanations in the form of "what needs to be changed in the input data to change the output" are useful for evaluating alternatives, sensitivity, and decision making
Hybrid and combined approaches (e.g., interpretable + complex model; surrogate -model + visualization; combined explanations)	can be either intrinsic (for a part) + post -hoc	both globally and locally	both model- -specific (for the interpretable part) and model- -independent	A balance between accuracy and interpretability; allows the use of powerful models while maintaining explanatory power

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Quality and limitations of XAI explanations. A review of XAI applications in industry/manufacturing found a strong trend toward using local, model-independent methods (in particular, SHAP) for predictive maintenance, process optimization, product quality management, and supply chain management [7]. Another aspect is assessing the quality of the explanations themselves. In the work " To trust or not to trust an explanation : using LEAF to evaluate local In a recent review of linear XAI methods , it was shown that popular methods, LIME and SHAP, can be unstable: their explanations are variable, may not meet the promised theoretical properties, and sometimes explain the "wrong" class. This highlights the need for careful application of XAI and standardized approaches to evaluating explanations [8]. Furthermore, a recent review for cardiology noted that many studies either do not evaluate XAI at all or evaluate it subjectively, which limits confidence in the explanations [9].

The following points are important for management tasks and decision-making:

1. The method should be chosen based on the goals: if a simple report and transparent rules are needed, then interpretable models are suitable; if high accuracy is required with complex data, then post-hoc methods are suitable.
2. Often, an explanation is required not for a single solution, but for a general model, in which case global explanations (e.g., aggregated SHAP, surrogate models) are preferable.
3. Interaction with domain specialists (managers, management) requires a convenient explanation format: visualization, clear rules, or "what if" scenarios.
4. It is necessary to assess the robustness of explanations , their adequacy, and their credibility. This requires not only an XAI tool but also a system for assessing the quality of explanations.

Thus, the taxonomy of XAI methods is an important theoretical and methodological foundation for the practical application of explainable AI. The division into intrinsically Interpretable and post-hoc methods, as well as consideration of criteria such as locality/globality, model independence/specificity, and explanation format, help researchers and practitioners select approaches best suited to specific tasks, explainability requirements , and constraints. It is important to remember that no single method

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is universal; it is important to combine methods, adapt them to the domain, and evaluate the quality and robustness of explanations.

XAI in management decisions and business. Modern business systems increasingly use machine learning (ML) and AI methods to support management decisions, from credit scoring and risk management to fraud detection and operational optimization. However, the "black box" nature of many models poses a challenge: how to ensure that automated decisions are fair, objective, compliant with laws and internal company policies, and understandable to stakeholders. This is where Explainable comes in. Artificial Intelligence (XAI): It ensures transparency, explainability, and interpretability of model decisions, which increases trust, facilitates auditing, complies with regulatory requirements, and helps business managers make informed decisions. We've examined the key applications of XAI in business and management.

Main areas of application:

1. Credit Scoring and credit risk assessment. One of the most frequently cited application scenarios for XAI is credit risk assessment: banks and fintech companies are increasingly turning to complex machine learning models (e.g., gradient boosting), but are still required to justify their decisions: who received the loan, why, on what grounds, and what the risk factors are. A paper on credit risk has shown that XAI (e.g., using feature contributions) can be used to ensure decision transparency and group borrowers by financial characteristics (and, consequently, by risk) for further analysis [10].
2. Risk management and financial decision management. A wide range of financial tasks, from portfolio management and operational risk management to fraud detection, can benefit from model explainability. For example, a recent study describes an approach that uses XAI (for fraud detection), while providing “user-centered” explanations for external stakeholders (regulators, clients), which increases trust and transparency [11].
3. Incorporating XAI into corporate analytics and management-level decision making. According to consulting companies and analysts, one of the values of XAI is that business teams (not technical specialists) can understand why the model makes certain decisions and see the connections between business goals

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and an algorithm, which facilitates the verification of hypotheses, adjustment of strategies, audit, control and risk assessment [12].

4. Regulatory and ethical compliance, accountability, and trust. In the US and other jurisdictions, the use of automated decisions (particularly in lending, insurance, and financial services) is often regulated by laws requiring explanations of decisions, especially in the case of negative outcomes (loan denial, rate increase, insurance denial). XAI ensures explainability of decisions, which promotes compliance with legal and ethical standards and reduces the risk of legal claims, reputational damage, and internal resistance.

For example , in The paper "Explainable Machine Learning in Credit Risk Management" shows how With help XAI (using, in particular, the contribution of features) can be used to analyze credit scoring models on peer-to-peer platforms, group applications from small and medium-sized enterprises by financial characteristics, and explain why the model classified some as “risky” and others not [10].

In a study focusing on fraud In fraud detection, an approach was developed that provides not just a "prediction: fraud/not fraud," but an "explanation" of what exactly in the data raised suspicion. This is important if regulatory authorities or clients want to understand the reason for a refusal, suspicion, or blocking [11] .

In a publication examining “Explainable AI in Fintech Risk In “Management”, the authors demonstrate how XAI helps fintech companies assess credit and operational risks while remaining transparent and meeting the expectations of investors and regulators [13].

Also, advisory materials for businesses emphasize that the use of XAI is not just a technical step, but an organizational one: business teams, risk managers, auditors, and compliance departments are involved at early stages, requirements for explainability are described, and monitoring, auditing, and feedback processes are formed [14].

Benefits of using XAI in business:

- increasing trust in AI solutions among executives, clients, and regulators.
- the ability to audit, explain and justify decisions, critical for lending, insurance, and regulated industries.

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- improving the transparency of business processes, facilitating communication between technical and business teams.
- assistance in identifying errors, biases , and injustices, which allows for adjustments to the model or policy.

Limitations of XAI application in business:

- explanations may be difficult for non-technical users to understand; they need to be translated into business language and interfaces adapted. This is emphasized in the work " On Two XAI Cultures ”, which describes the problem: often what is considered “explanation” for developers remains unclear for managers or regulators [15].
- in a number of cases, limitations in stability and usefulness: in an experiment evaluating explanations (for example, using SHAP), it is not always possible to demonstrate that explanations actually change people's decisions, as, for example, in the task of processing " alerts ", explanations did not significantly improve the quality of decision-making compared to just a label/prediction.
- costs of integration, support, audit, interfaces; sometimes the involvement of additional specialists (compliance, lawyers, UX designers) is required to ensure adequate explanation.

Table 2 - Scenarios for applying XAI in business and management

Scenario / application area	**Task type / business -goal**	**Example of a model/ technology**	**The role of XAI / what it provides**	**Risks/Limitations**
Credit scoring , credit risk assessment	Loan issuance/refusal, default probability assessment	Gradient models boosting , decision trees + XAI (SHAP, LIME)	Explanation of reasons for refusal/approval, transparency, audit, fairness	Complexity of explanation for clients/regulators; computational costs.
Financial management, risk -manageme nt, portfolio management	Risk assessment, control, investment decision making	Random Forest , ensembles, machine learning models + XAI	Identification of key risk factors, decision support, adaptation of strategies	Possible instability of explanations, need to refine the model.
Fraud detection detection)	Identifying suspicious transactions, preventing losses	Classifiers + XAI	Explanation of the trigger reasons is important for clients, regulators, and audit	Explanations may not be clear enough for non-technical stakeholders.
Corporate analytics and management decision making	Process optimization, forecasting, strategic planning	Various MO + XAI models	Simplify communication between technical and business -units; make informed decisions	Explanations need to be adapted to business -language ; implementation is labor-intensive .
Compliance , regulatory requirements, audit	Compliance with laws, transparency of decisions, protection of customer rights	MO + XAI models	Documenting decisions, explaining to regulators/auditors, mitigating legal and reputational risks	Stability of explanations and clarity are required, audit is resource-intensive .

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XAI Implementation Principles. To successfully use Explainable AI (XAI) in business and management, it's important not only to select methods but also to integrate them into decision-making processes, ensure user understanding, and control the quality of explanations.

Formal Model of the XAI Integration Pipeline

The process of integrating XAI into managerial analytics can be represented as a sequence of transformations:

$$D \to f \to \hat{y} \to E \to \mathcal{E} \to U \to R,$$

where

D – input data,

f – trained machine learning model,

$\hat{y}$ – model predictions,

E – XAI method,

$\mathcal{E}$ – set of explanations,

U – user interpretation (manager, analyst),

R – managerial decision.

Formula 3. Formal representation of the XAI integration pipeline

Thus, XAI acts as an intermediate layer between algorithmic predictions and the decision-making process, ensuring transparency, interpretability, and control over model-driven decisions.

Based on the analysis of literature and practice, the following key principles are identified:

1. Purpose and audience: to determine which decisions require explanations and for whom.
2. Choice of method: simple tasks - transparent models; complex tasks - post-hoc methods (SHAP, LIME).
3. Integration and visualization: Provide explanations in an understandable form through reports, dashboards or scenario tools.

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4. Evaluation and control: check the stability and usefulness of explanations; conduct user training.

These principles ensure transparency, trust, and validity of AI-based decisions in management processes.

Conclusion

Therefore, the use of XAI in business and management tasks is not just a "technical trick", but a strategic tool that: reduces barriers to trust in automated decisions; facilitates interaction between technical and non-technical participants: managers, auditors, regulators; increases the transparency, accountability, and fairness of AI-based decisions; helps identify and correct risks, errors, and biases; and makes AI decisions part of corporate responsibility and compliance practices. It's important to understand that XAI is not a "magic bullet": it requires thoughtful integration, proper configuration, evaluation of explanations, adaptation to the business context and user expectations, as well as ongoing auditing and support.

References

1. Dey N., Ashour AS, Balas VE Explainable Artificial Intelligence: Concepts, Applications and Challenges. International Journal of Artificial Intelligence and Machine Learning, 2021. URL: https://itaimle.com/index.php/ijaiml/article/view/209 (date accesses:11/28/2025).
2. Emergent Society. Explainable AI in Modern Decision Making. Emerging Society Journal, 2021. URL: https://emergingsociety.org/index.php/efltajet/article/view/274 (date accesses: 11/28/2025).
3. Ouçi DNTB Explainable AI Methods: A Comprehensive Review. OUCI, 2021. URL: https://ouci.dntb. gov.ua / en / works /4 awDwZN 9/ (accessed: 29.11.2025).
4. Arrieta AB, Díaz -Rodríguez N., Del Ser J. et al. Explainable Artificial Intelligence (XAI): Concepts, Taxonomies, Opportunities and Challenges. arXiv preprint, 2022. URL: https://arxiv.org/abs/2201.08164 (date accesses: 29.11.2025).

Modern American Journal of Engineering, Technology, and Innovation
ISSN(E): 3067-7939
Volume 01, Issue 09, December, 2025
Website: usajournals.org

5. Schwalbe K., Finzel K. A Comprehensive Taxonomy for Explainable Artificial Intelligence: A Systematic Survey. arXiv preprint, 2021. URL: https://arxiv.org/abs/2105.07190 (date accesses: 29.11.2025).
6. Guidotti R., Monreale A., Ruggieri S. et al. A Survey of Methods for Explaining Black Box Models. ScienceDirect , 2018. URL : https :// www . sciencedirect . com / science / article / pii / S 1566253519308103 (accessed: 30.11.2025).
7. Singh D., Kumar P., Prakash C. Application of Explainable AI in Industry 4.0. Springer , 2025. URL: https://link.springer.com/article/10.1007/s42452-025-07908-z (date accessed: 30.11.2025).
8. Slack D., Hilgard S., Jia E. et al. Fooling LIME and SHAP: Adversarial Attacks on Post hoc Explanation Methods. arXiv preprint, 2021. URL: https://arxiv.org/abs/2106.00461 (date accesses : 30 .1 1 .2025).
9. Doshi -Velez F., Kim B. Towards a Rigorous Science of Interpretable Machine Learning. Springer , 2024. URL: https://link.springer.com/article/10.1007/s10462-024-10852-w (accessed 12/01/2025).
10. Galindo J., Tamayo P. Credit Risk Assessment Using Explainable Machine Learning. Springer , 2020. URL: https://link.springer.com/article/10.1007/s10614-020-10042-0 (accessed 12/01/2025).
11. Jabeur N., Ben Abdessalem K., Dhaouadi R. Fraud Detection in Financial Transactions Using Explainable AI. ScienceDirect, 2023. URL: https://www.sciencedirect.com/science/article/abs/pii/S1544612323006815 (date accesses: 01.12.2025).
12. McKinsey & Company. Why Businesses Need Explainable AI and How to Deliver It. McKinsey , 2022. URL : https :// www . mckinsey . com / capabilities / quantumblack / our - insights / why - businesses - need - explainable - ai - and - how - to - deliver - it (date accessed: 12/01/2025).
13. Alsheikh A., Nair S., Raut R. Explainable AI in Fintech Risk Management. PMC , 2021. URL : https :// pmc . ncbi . nlm . nih . gov / articles / PMC 7861223/ (accessed: 02.12.2025).
14. Berger Team . Explainable AI (XAI) for Enterprises: Implementation Guidelines. Berger Team, 2022. URL : https :// www . berger . team / ru /

Modern American Journal of Engineering, Technology, and Innovation
ISSN(E): 3067-7939
Volume 01, Issue 09, December, 2025
Website: usajournals.org

kuenstliche - intelligenz / explainable - ai - erklaerbare - kuenstliche - intelligenz - fuer - unternehmen (accessed: 02.12.2025).

15. Holstein K., Wortman Vaughan J., Daumé III H. et al. Improving Fairness in Machine Learning Systems: What Do Industry Practitioners Need? arXiv preprint, 2021. URL: https://arxiv.org/abs/2112.01016 (access date: 12/02/2025).