SILESIAN UNIVERSITY OF TECHNOLOGY PUBLISHING HOUSE

SCIENTIFIC PAPERS OF SILESIAN UNIVERSITY OF TECHNOLOGY 2026
ORGANIZATION AND MANAGEMENT SERIES NO. 253

# TRIANGULATION OF AI MODELS FOR ANOMALY DETECTION IN ENTERPRISE MANAGEMENT PROCESSES

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**Purpose:** The objective of this study is to understand and assess the effectiveness of triangulating artificial intelligence (AI) models for detecting financial anomalies in enterprise management processes, with particular emphasis on the role of managerial, organizational, and decision-making context in the interpretation of results generated by AI models.
**Design/methodology/approach**: The study employs a mixed-methods approach, combining a structured literature review with a single exploratory-explanatory case study. Quantitative data were obtained from the ERP system of the analyzed enterprise and processed using six state-of-the-art AI models. The outputs were subsequently compared and synthesized to identify convergent and divergent analytical patterns across models.
**Findings:** The findings indicate that the analyzed AI models were able to identify several unusual financial patterns, including distorted turnover indicators, high B2B-related costs, and changes in receivables and inventory cycles. However, without detailed managerial and organizational context, the models frequently misclassified planned investments, legal transformation effects, and accounting adjustments as negative business anomalies.
**Practical implications:** The study suggests that organizations should not rely on AI-driven anomaly detection systems as standalone decision-support tools. Instead, effective implementation requires integrating AI outputs with managerial expertise and organizational context. This implies the need for hybrid decision-making frameworks, redesigned control processes, and enhanced managerial competencies in interpreting AI-generated insights.
**Social implications**: This study highlights the risks of relying on AI-driven anomaly detection without sufficient organizational context. The findings show that overdependence on AI may lead to misinterpretation of financial data and flawed managerial decisions.
**Originality/value:** This study provides original value by examining the limitations of AI model triangulation for financial anomaly detection in enterprise management. By comparing six state-of-the-art AI models and an aggregated synthesis approach, it demonstrates that triangulation alone does not overcome the lack of organizational and decision-making context, challenging the assumption that combining multiple AI models necessarily improves analytical outcomes.
**Keywords:** enterprise management, AI model triangulation, anomaly detection.
**Category of the paper:** Case study.

## 1. Introduction

The implementation of artificial intelligence models in enterprise management processes has led to the increasing use of machine learning and deep learning algorithms for monitoring operational efficiency, financial control, and supporting managerial decision-making. A particularly important role is played by AI models for anomaly detection, which enable the identification of unusual deviations in financial, process, and organizational data, often at a very early stage of their occurrence (Chandola et al., 2009; Pang et al., 2021). Under conditions of growing organizational complexity, process digitalization, and high volatility of the economic environment, the ability to rapidly detect anomalies becomes a key element of early warning systems and risk management (Davenport, Ronanki, 2018; Wamba et al., 2021). At the same time, it should be noted that individual AI models, although statistically effective, often generate results that are prone to overinterpretation, especially when the analyzed data are strongly dependent on specific decisions or incidental events.

In this context, the triangulation of AI models is gaining increasing importance, understood as the combination of results from multiple algorithms, different analytical perspectives, and contextual knowledge in order to enhance the accuracy of interpreting detected anomalies. Triangulation has long been recognized as a methodological approach in management sciences and social sciences, serving to reduce cognitive biases and strengthen the credibility of research conclusions (Denzin, 2017). However, an analysis of the current literature indicates that this concept remains underdeveloped in research on the application of AI to anomaly detection in enterprise management processes, where technical approaches focused on the performance of individual models still dominate (Ruff et al., 2021). The lack of integration of multiple AI models and the managerial perspective may lead to misdiagnosis of a company's financial condition and inappropriate strategic decisions. According to the concept of Human-Centered Artificial Intelligence, AI models should serve to enhance decision-making capabilities rather than replace human judgment, particularly in situations where decision risk is high (Shneiderman, 2020). For this reason, the triangulation of AI models currently constitutes an important and timely research direction, combining technological development with the need for responsible, contextual, and human-centered enterprise management (Mikalef et al., 2022).

Therefore, this study poses the following research question: to what extent are AI models able to distinguish between unusual financial patterns and genuinely negative managerial anomalies when detailed organizational and decision-making context is not available during the initial analysis? As a consequence of this research question, the following hypothesis was adopted: artificial intelligence models can identify selected unusual patterns in enterprise financial data but when detailed managerial and organizational context is unavailable, they may misclassify planned investments, legal transformation effects, and accounting adjustments as negative business anomalies. The aim of this study is to fill the identified research gap by

deepening the understanding and assessing the capabilities of artificial intelligence models used for detecting financial anomalies in enterprise management processes, as well as by determining the importance of decision-making and organizational context, possessed by humans, in the process of interpreting the results generated by these AI models.

## 2. Literature review

The advancement of artificial intelligence models in enterprise management processes has increased significantly over the past decade, evolving from analytical support to active participation in decision-making processes. Research indicates that AI is currently being integrated into key management functions such as strategic planning, management control, operational management, and risk analysis, leading to the transformation of traditional management models toward data-driven models (Davenport, Ronanki, 2018; Haenlein, Kaplan, 2019). Systematic literature reviews emphasize that the dominant applications of AI in enterprises include machine learning and deep learning used for forecasting, classification, and process optimization, with particular importance attributed to the integration of AI with ERP and Business Intelligence systems (Kraus et al., 2022; Raina et al., 2024).

Contemporary AI models used in management are characterized by an increasing level of autonomy and adaptive capability, which affects the structure of decision-making within organizations. The literature indicates that AI not only supports managers in data analysis but increasingly assumes decision-making functions in operational and tactical areas such as inventory management, resource allocation, and dynamic production planning (Shrestha et al., 2019; Wamba et al., 2021). At the same time, the importance of Explainable AI (XAI) solutions is emphasized, as they enhance algorithmic transparency and enable their application in contexts requiring decision accountability and managerial control (Mikalef et al., 2022). This signifies a transition from decision support tools to co-decision systems, which has significant implications for management theory.

An important area of AI application in enterprise management is anomaly detection, understood as the identification of unusual deviations in process, financial, and operational data. Research shows that AI-based methods significantly outperform traditional rule-based approaches, particularly under conditions of high data complexity and dynamics (Chandola et al., 2009; Pang et al., 2021). The literature is dominated by techniques such as autoencoders, LSTM models, Isolation Forest, and hybrid deep learning models, applied mainly in technical contexts (e.g., IT systems, IoT, cybersecurity) and in finance (Ruff et al., 2021). From the perspective of enterprise management, however, anomaly detection is increasingly perceived as an element of operational intelligence and management control, enabling early

detection of risks, inefficiencies, and undesirable behaviors (Bose, Mahapatra, 2019; Appelbaum et al., 2017).

However, the analysis of the literature reveals a clear research gap concerning the application of AI model triangulation for anomaly detection in enterprise management processes. While triangulation of methods and data sources is a well-established methodological practice in management sciences (Denzin, 2017), research on anomaly detection focuses mainly on single models or ensembles of algorithms evaluated in terms of technical performance rather than cognitive complementarity in an organizational context. Decision-making processes, both human and algorithmic, are exposed to simplifications and interpretative biases, which justifies the need to reduce the risk of overinterpretation through the application of solutions such as triangulation of analytical sources (Kahneman, 2011). Consequently, there is a lack of studies that integrate different AI models, different data levels (strategic, operational, financial), and the managerial decision-making perspective within a coherent triangulation approach. This opens an important direction for further research, particularly at the intersection of quantitative methods, strategic management, and intelligent decision support systems (Janssen et al., 2020).

## 3. Methodology

The study was designed as a single-case study of an exploratory-explanatory nature, which is an approach recommended for the analysis of complex decision-making processes that are strongly embedded in an organizational context and cannot be clearly separated from the research environment (Eisenhardt, 1989; Yin, 2018). The unit of analysis was the process of managerial decision-making supported by artificial intelligence assistants in a trading company that, in the years 2023-2025, underwent a transformation of its management processes from an approach based on employed sales representatives to an approach based on B2B cooperation. The application of the case study paradigm was justified both by the uniqueness of the analyzed transformation and by the necessity of incorporating contextual knowledge into the interpretation of financial analysis results.

The analyzed organization was a Polish trading company specializing in the sale of tools and metal fasteners. Its product portfolio is combined with fast-moving items, such as screws, nuts, with slower-moving specialized tools, including automotive tools. This product mix made working-capital indicators particularly sensitive to changes in sales structure, purchasing policy, stock levels, and the pace of inventory rotation. Before the transformation, the company generated approximately PLN 26.8 million in revenue in 2023. During the legal and operating transition in 2024, annual revenue temporarily declined to approximately PLN 68 thousand. In 2025, revenue recovered to approximately PLN 5.55 million, although it remained

substantially below the pre-transformation level. The transition from an employment-based sales model to cooperation with independent B2B partners was undertaken in response to rising labour costs, the need to scale sales operations, and expressed employee interest in a B2B form of cooperation. The intended purpose was to reduce fixed employment costs while increasing the flexibility and scalability of sales activity. The transformation coincided with a change in the company's legal form, adjustments in accounting treatment, modifications to the incentive system for sales partners, and changes in the sales profile. These overlapping changes created a suitable setting for examining the difference between the initial identification of unusual financial patterns and their subsequent managerial interpretation.

The primary source of quantitative data consisted of monthly financial and operational data obtained from the ERP system and the financial and accounting system of the analyzed enterprise. These data included the income statement, balance sheet, cash flows, and key financial indicators such as operating margin, EBITDA, DSO, DPO, and DIO. The data formed the basis for analyses conducted by artificial intelligence models and enabled the identification of trends and deviations during a period of intensive organizational and financial change. In this study, anomaly identification and managerial interpretation were treated as analytically distinct stages. Anomaly identification referred to a model explicitly flagging an unusual value, trend, or pattern in the reported financial and operational data, including abrupt changes in profitability, DSO, DPO, DIO, inventory turnover, cost ratios, or financing structure. This stage did not involve a formal statistical anomaly-detection algorithm but rather, it concerned the identification of unusual patterns by the analyzed AI models on the basis of the supplied financial data. Managerial interpretation referred to the subsequent assessment of whether a detected deviation represented a negative business event requiring corrective action or an expected consequence of a managerial decision, planned investment, legal transformation, accounting adjustment, or temporary reporting distortion. The study therefore assessed not only whether AI models identified unusual financial patterns, but also whether they interpreted their managerial significance adequately after confrontation with organizational documentation and managerial evidence. The use of real financial data is consistent with the stream of research on the application of AI as a tool supporting data-driven management (Davenport & Ronanki, 2018; Wamba et al., 2021).

The second category of data consisted of analytical results generated by six advanced artificial intelligence models: ChatGPT 5.1, Claude Sonnet 4.5, Gemini 3 Pro, Grok 4.1, Kimi K2, and Sonar. Each of the listed AI models conducted its analysis based on the same description of the business situation of the analyzed enterprise, its financial statements, and the set of financial indicators mentioned above. The results of the analyses were evaluated on a scale from 1 to 10, representing a variant of an ordinal Likert-type scale that allows the results to be treated as quasi-quantitative variables (Norman, 2010). The analyzed AI models were evaluated according to four categories: analysis time, level of analytical detail, quality of diagnosis, and quality of proposed solutions. Subsequently, the Perplexity Pro assistant was

used to create an aggregated synthesis of the results, taking into account both shared conclusions and unique insights generated by individual models.

Combining the outputs of multiple AI models makes it possible to reduce the interpretative errors of a single algorithm and to increase the credibility and stability of analytical conclusions (Dietterich, 2000). Each model received an identical set of financial data and a standardized research prompt, including the analysis of financial indicators, identification of anomalies, assessment of potential risks, and formulation of managerial recommendations. Information was collected on the number and nature of detected anomalies, periods identified as problematic, and the tone and direction of recommendations. This approach enabled a comparison of interpretative consistency and divergence among AI models, as well as an assessment of their usefulness in the decision-making process, in line with the literature indicating the growing role of AI in organizational decision structures (Shrestha et al., 2019).

To improve transparency and replicability, all AI models received the same standardized analytical instruction and the same set of financial statements, operational indicators, and basic business-context information. No model-specific prompt tuning was applied, apart from technical formatting adjustments required by individual platforms. The standardized prompt is reproduced in Appendix B.

An important complement to the quantitative and algorithmic data was qualitative data obtained in the form of an in-depth semi-structured interview with a decision-maker, as well as an analysis of documents and managerial notes created during work with AI assistants. These data concerned, in particular, planned investments in the final months of the analyzed years, the formal transformation of the legal form of the analyzed enterprise, and changes in accounting principles and sales profile. Their purpose was to capture contextual knowledge that made it possible to explain why anomalies identified by AI models, such as significant declines in margins in December or distorted values of turnover ratios during the transformation period, did not constitute signals of a deteriorating financial condition, but rather were consequences of rational and planned strategic decisions. The inclusion of the managerial perspective is consistent with the assumptions of the Human-Centered AI concept, according to which AI plays a supporting role rather than replacing human decision judgment (Mikalef et al., 2022).

The entire data collection process was based on the principle of source triangulation, combining financial data, results generated by AI models, and expert knowledge together with organizational documentation. Such an approach increases the construct validity of the study and enables the development of causal explanations through pattern matching and explanation building (Yin, 2018). Triangulation is particularly important in anomaly detection research, as statistical deviations do not always indicate economic problems, and their correct interpretation requires consideration of decision-making and organizational context (Denzin, 2017). Moreover, systems supporting enterprise management processes should take into account stakeholder values and objectives, rather than focusing exclusively on the optimization of technical or economic indicators (Friedman et al., 2006).

For confidentiality and data-protection purposes, the financial and operational data supplied to the AI models were anonymized, and no personal data relating to employees, customers, or B2B partners were included in the model inputs. The AI-generated outputs were treated solely as analytical decision-support material and were interpreted in conjunction with managerial interview evidence and organizational documentation rather than as autonomous managerial conclusions.

## 4. Results

In the first phase of the empirical study, six AI models were examined in order to understand and assess the capabilities of artificial intelligence models used for detecting financial anomalies in enterprise management processes. The analyzed AI models were tasked with conducting an analysis of a set of financial indicators of the examined enterprise. The analysis of the indicators was required to take into account four categories of criteria, which are presented in Table 1.

**Table 1.**
*Results of comparative analyses*

| AI Model | Category | | | | Overall score |
|---|---|---|---|---|---|
| | Analysis time | Analytical depth | Diagnostic quality | Quality of recommendations | |
| ChatGPT 5.1 | 6.5 | 10 | 10 | 10 | 9.13 |
| Claude Sonnet 4.5 | 7.5 | 9 | 8.5 | 9 | 8.5 |
| Gemini 3 Pro | 8 | 8 | 7.5 | 7 | 7.6 |
| Grok | 8.5 | 6.5 | 6.5 | 6 | 6.88 |
| Kimi k2 | 10 | 6 | 5 | 5 | 6.5 |
| Sonar | 8.5 | 4 | 4 | 3 | 4.88 |

Source: authors' own elaboration based on the evaluation of the obtained results.

In the second phase of the empirical study, a controlled experiment was conducted (Table 2) with the aim of comparing the highest-rated model, ChatGPT 5.1 (average score 9.13), with the aggregated synthesis of models. The single AI model identified 9 out of 12 key problems, whereas the synthesis detected all 12. Unique insights generated by the aggregated model included issues related to debt collection, a faulty B2B incentive system (excessively high annual bonuses), and risks associated with the refinancing of liabilities. The analysis generated by ChatGPT regarding high B2B costs suggested that their cause was incorrect cost aggregation. The Claude model indicated a faulty subcontractor commission mechanism as the source of high B2B costs, while the Gemini model pointed to a lack of cost control, and the Grok model suggested possible data manipulation within the ERP system. The synthesis of all perspectives made it possible to formulate both an audit plan and a managerial action plan.

**Table 2.**
*Consistency matrix among the analyzed AI models*

| Anomaly | Analyzed AI model | | | | | | Accordance |
|---|---|---|---|---|---|---|---|
| | ChatGPT | Claude | Gemini | Grok | Kimi | Sonar | |
| Disorted indicator values | X | X | X | X | X | X | **6/6** |
| High B2B costs | X | X | X | X | X | - | **5/6** |
| Decline in inventory turnover | X | X | X | X | - | - | **4/6** |
| Deterioration of receivables collection | X | X | X | - | - | - | **3/6** |

Source: authors' own elaboration based on analyses conducted by LLM models.

In the third phase of the empirical study, convergence in managerial recommendations was examined for actions proposed by the AI models. Table 3 reports the number and proportion of models explicitly proposing each selected recommendation. The strongest convergence concerned the reduction or reengineering of fixed and operating costs, recommended by all six models, followed by inventory management optimisation, proposed by five of the six models.

**Table 3.**
*Consistency of recommendations among AI models*

| Recommendation | Number of AI models | Accordance | Implementation priority |
|---|---|---|---|
| Reduction of fixed costs | 6/6 | 100% | Critical |
| Optimization of inventory management | 5/6 | 83% | High |
| Hybrid model (B2B partners + sales representatives assigned to key partners) | 4/6 | 67% | Medium |
| Receivables management | 4/6 | 67% | Medium |
| ERP data audit and correction of financial indicator formulas | 3/6 | 50% | Medium |

Source: authors' own elaboration.

Moderate convergence was observed for receivables management and sales-model redesign (including hybrid channel approaches), each recommended by four of the six models, while ERP data auditing and correction of financial indicator formulas showed comparatively lower convergence, being explicitly proposed by only three of the six models. These results are reported as descriptive evidence of similarity in model outputs and do not establish the factual correctness of the recommendations or the overall reliability of the triangulation procedure. The complete coding matrix underlying the descriptive analysis of recommendation convergence is provided in Appendix A.

Analyses conducted using AI models indicate that, in the examined enterprise, the transformation focused on the B2B approach resulted simultaneously in three key phenomena. First, profit potential still exists, particularly in 2025, when gross margins remained at the level of 24-29%. This indicates that the B2B concept itself, larger volumes, lower customer acquisition costs, and deeper cooperation, is market-viable. Second, the scale of operations collapsed significantly in 2024 (from approximately 26.8 million PLN in 2023 to only 68 thousand PLN), before partially recovering in 2025 to 5.55 million PLN, which represents 20% of the pre-transformation potential. Most of the analyzed AI models consistently indicated that the enterprise "passed through the valley of death", typical for

reorganizations, but did not recover to full operational capacity. Third, the values of operational indicators became extremely unstable: the operating margin fluctuated from +31% to –34% in 2024, and another decline (–22%) was recorded in December 2025. Such strong fluctuations suggest errors in cost monitoring, annual write-offs, accounting issues, or a lack of control over B2B partner costs.

The AI models also revealed a number of serious problems. One of the most significant is the unreliability of accounting data and financial indicators, especially in January 2024, when the days sales outstanding (DSO) reached 1443 days, days payables outstanding (DPO) 2080 days, and days inventory outstanding (DIO) 311 days. It should be noted that these are not decision-making errors at the enterprise management level, but rather errors at the ERP system level. A shared conclusion generated by the AI models was as follows: without correct data, managing the transformation does not provide a clear and reliable picture of the financial condition of the analyzed enterprise. Another issue is that B2B costs turned out to be higher than the costs associated with an approach based on salaried sales representatives. In 2023, employees generated costs amounting to 19% of revenues, whereas in December 2025 B2B partners absorbed 37% of revenues (829 thousand PLN out of 2.2 million PLN). Thus, the new approach is more expensive and less efficient at a smaller sales scale, and the operating margin fell to values close to zero or negative. The increase in inventory levels and the decline in turnover (inventory cycle from 3 to 22 days) were also signals of deteriorating supply chain management quality.

According to the Grok and Gemini models, the new approach requires greater planning precision, and B2B sales partners may introduce products to the market that rotate much more slowly. An equally important issue is the incentive system for B2B partners: the receivables cycle (DSO) increased from 5 to approximately 50 days, indicating significantly worse collection effectiveness than in the case of salaried sales representatives. The Gemini model pointed to a poorly designed bonus system that rewards invoice issuance rather than actual cash inflows from sales, leading to payment backlogs. In addition, there is the issue of financing the operations of the analyzed enterprise: the share of equity capital fell to 9.5% of the balance sheet, which is a level typical of enterprises in a zone of increased insolvency risk. Dependence on liabilities to suppliers has become a short-term mechanism stabilizing the financial situation, which may cease to function at any moment.

The analysis also identified several additional anomalies. First, recurring declines in operating margins are noticeable in December 2024 and 2025, which may result from accounting policies related to write-offs, provisions, and annual postings. Second, December 2025 revealed a sharp increase in B2B partner commission costs, which reached 829 thousand PLN in a single month. The models suggested various possible causes: very high bonuses, incorrect cost aggregation, or a faulty commission mechanism. Third, January 2024 was characterized by distorted financial KPI results, which suggests critical errors in input data rather than managerial decision-making.

Most AI models converged on the general direction of corrective actions. Therefore, a single consolidated recovery plan was developed. In the immediate horizon (0-30 days), the following are necessary: an audit of ERP data and correction of financial KPI formulas, a detailed audit of B2B partner costs, especially commissions for December 2025, and the introduction of a debt collection system based on commissions for cash inflows rather than issued sales invoices. Within 1-3 months, the enterprise should reduce fixed costs by 10-15%, optimize inventories using inventory and cost optimization methods to achieve an inventory cycle below 15 days, and introduce a new pricing policy combined with the elimination of customers with margins below 15%. In the short-term perspective (3-12 months), most AI models recommended considering a hybrid sales model, in which B2B partners serve regular customers, while salaried sales representatives handle key partners. It is also necessary to strengthen equity capital through profit retention, owner contributions, or refinancing of costly short-term liabilities.

Interestingly, the final conclusions of all AI models were characterized by high consistency. The B2B transformation is not a failure, it is incomplete and insufficiently refined. The potential is significant, but the current form generates more risk than value. The strategy is sound, but execution requires substantial improvement. There is potential to increase margin levels. To achieve the increase of margin levels, the scale of operations must increase to at least half of the 2023 level, and the greatest risks are financial liquidity and the level of B2B costs, which are too high relative to the achieved outcomes. If the enterprise implements the recommended changes, the B2B approach may deliver higher profitability, greater operational scale, lower acquisition costs, and more predictable margins. It should be emphasized that the key conclusion of AI models in detecting anomalies in enterprise management processes is that without organized data and properly designed incentive systems, an effective enterprise management process will not function, regardless of whether sales are carried out by salaried sales representatives or B2B partners.

## 5. Discussion

This study was based on the assumption that artificial intelligence models used to detect anomalies in a company's financial data may misjudge the financial condition of the enterprise if they do not take into account the business context of the conducted activities. The results of the conducted research suggest that the triangulation of AI models for anomaly detection in enterprise management processes made it possible to identify numerous anomalies appearing in the financial statements of the analyzed enterprise. This was particularly evident during the period of annual financial closing, which the AI models described as "December black holes". However, these deviations did not result solely from operational errors but had real business

justifications. Each year, the analyzed enterprise made significant purchases of fixed assets in December, thereby utilizing the financial surplus accumulated in the final months of the year. Nevertheless, economic events related to the acquisition of new equipment generate high costs, which reduce operating margin and EBITDA in December, creating a "collapse" effect that AI models detected as an anomaly. From a managerial perspective, these were planned and controlled investment activities of the analyzed enterprise rather than signals of deteriorating financial condition.

The second category of anomalies identified by all applied AI models consisted of distorted values of the days sales outstanding (DSO), days payables outstanding (DPO), and days inventory outstanding (DIO) indicators, particularly visible in January 2024. The obtained results did not stem from improperly conducted operational activities but were a consequence of the formal transformation of the enterprise. The analyzed company was transformed from a sole proprietorship into a limited liability company, which required the transfer of assets, balance sheet balances, and the redefinition of accounting principles. This means that the transformation period contributed to the distortion of results obtained using financial indicators, especially when initial sales or costs in the new organizational structure were close to zero. In such cases, ratio-based indicators (turnover ratios) react by generating unrealistic values that do not reflect the actual operational situation of the enterprise.

From an analytical perspective, it is worth emphasizing that both identified sets of anomalies, December margin declines and unrealistic financial indicator values during the transformation period, have logical and fully justified origins. Understanding their nature makes it possible to avoid misinterpretation of data and enables a more reliable assessment of the effectiveness of the transformation and the financial condition of the enterprise.

The research results concerning the triangulation of AI models for anomaly detection confirm their usefulness as advanced tools supporting enterprise management processes. The analysis of six AI models demonstrated that artificial intelligence is capable of rapidly identifying not only basic financial trends but also anomalies, deviations, systemic errors, and potential risks, the identification of which in traditional reporting processes often requires significant time and effort.

A clear implication derived from the theoretical assumptions and the conducted research is that the key condition for the effective use of AI in detecting anomalies in enterprise management processes is the quality and completeness of input data. A decision-maker with full access to financial, operational, and system data must ensure the accuracy and consistency of the data that form the foundation of any analysis. Modern ERP systems provide such data directly, however, how these data are utilized depends on decision-makers. In contrast, the conducted research showed that although AI models are capable of indicating problems occurring in enterprise management processes, they cannot replace the contextual knowledge of a manager. The AI models frequently identified unusual financial and operational patterns. However, the adequacy of their interpretation varied across models and required verification against managerial knowledge, organizational documentation, and accounting context.

## 6. Conclusion

Summarizing the considerations presented in this study, it is worth emphasizing that understanding and assessing the capabilities of artificial intelligence models used for detecting financial anomalies opens the way for enterprises to improve their management processes. The conducted research confirms that the application of AI model triangulation in enterprise management significantly increases the quality and speed of obtained analyses and proposed solutions. The transformation of the enterprise's operational activity from a traditional sales-based approach to the implementation of solutions based on B2B partners proved to be an incomplete process requiring adjustments. Nevertheless, the multi-model analysis conducted using AI models enabled the rapid identification of financial anomalies and the detection of potential risks associated with the conducted business activity.

The main contribution of this article lies in its strong empirical evidence demonstrating that the application of AI model triangulation for anomaly detection shortens the time required to identify threats and formulate recommendations, which is particularly important for enterprises operating in environments characterized by dynamic change. The analyzed AI models were able to perform the analysis within a few minutes, whereas conducting such an analysis in a traditional manner would require many days of work by a financial team. The examined AI models offered different interpretative perspectives, which increased the depth of the analysis. However, caution should be exercised in the assessment of Human-Centered AI, as it does not replace the manager but rather provides diverse interpretations of data, facilitating the selection of appropriate decisions. Moreover, AI models in financial applications do not replace the decision-making process, instead, they radically accelerate its key stages by delivering multi-dimensional diagnoses, detecting anomalies, and proposing corrective actions. The use of AI model triangulation requires decision-making and organizational context, and defining this context necessitates managerial knowledge.

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# Appendix A

Complete coding matrix of standardized recommendation categories across AI models

| Code | Standardized recommendation category | ChatGPT | Claude | Gemini | Grok | Kimi | Sonar | Convergence |
|---|---|---|---|---|---|---|---|---|
| R1 | Audit ERP data integrity and correct KPI formulas | 1 | 1 | 0 | 0 | 1 | 0 | 3/6 |
| R2 | Audit the operating-cost structure, including B2B commissions where applicable | 0 | 1 | 1 | 1 | 1 | 0 | 4/6 |
| R3 | Reduce or reengineer fixed and operating costs | 1 | 1 | 1 | 1 | 1 | 1 | 6/6 |
| R4 | Review pricing and margin policy | 1 | 1 | 0 | 0 | 1 | 0 | 3/6 |
| R5 | Analyze customer and product profitability and rationalize the portfolio | 1 | 1 | 0 | 0 | 1 | 0 | 3/6 |
| R6 | Strengthen receivables management, including payment terms, incentives, or factoring | 1 | 1 | 1 | 1 | 0 | 0 | 4/6 |
| R7 | Optimize inventory management | 1 | 1 | 1 | 1 | 1 | 0 | 5/6 |
| R8 | Renegotiate supplier terms and manage payables | 1 | 1 | 1 | 0 | 1 | 0 | 4/6 |
| R9 | Refinance liabilities or strengthen equity capital | 0 | 0 | 0 | 0 | 0 | 1 | 1/6 |
| R10 | Introduce KPI monitoring, management reporting, dashboards, or forecasting | 1 | 1 | 0 | 1 | 0 | 1 | 4/6 |
| R11 | Automate or digitalize B2B, sales, or controlling processes | 0 | 1 | 0 | 0 | 1 | 0 | 2/6 |
| R12 | Redesign the sales model or diversify sales channels | 1 | 0 | 1 | 0 | 1 | 1 | 4/6 |

Note: Two authors independently coded the recommendation content of each AI output using the predefined coding framework. A recommendation was coded as present only when it was explicitly proposed by a model. Disagreements were resolved through discussion with reference to the original model output. he matrix therefore documents descriptive convergence in recommendation content and does not assess the factual correctness or managerial validity of the recommendations.

# Appendix B

**Standardized prompt used for all AI models**

"Analyze the attached monthly financial and operational data of a trading company for the period 2023-2025.
Identify unusual values, trends, and potential anomalies in:

1. profitability and operating margins,
2. liquidity and financing structure,
3. receivables and DSO,
4. payables and DPO,
5. inventory turnover and DIO,
6. cost structure, including B2B-related costs.

For each identified issue:

a. indicate the relevant period and financial indicator,
b. explain why the issue may be significant,
c. distinguish, where possible, between a potential data-quality problem and a managerial or operational problem,
d. provide possible explanations,
e. propose managerial corrective actions and indicate their priority.

Prepare the response in a structured form, distinguishing: key findings, detected issues, possible causes, and recommended actions".