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The Essential Role of Analytical Skills in AI-Powered Financial Systems: Methodology, Model Interpretation, and Performance Metrics

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Abstract

The article focuses on the evolution of analytical competencies in the environment of AI-driven financial platforms. The objective of the study is to systematize and analyze the process of transforming the set and content of analytical skills required by financial specialists for productive work with AI systems. The methodological foundation was a systematic review of specialized literature during which contemporary theoretical concepts and empirical industry trends were integrated. The findings indicate a shift in emphasis from routine computational abilities to higher-order competencies: critical verification of AI outputs, interpretation of multilevel models, management of black-box risks, and strategic decision-making. It has been established that true synergy is achieved not through human substitution but through the transformation of the human role into that of validator, strategist, and guarantor of ethical standards. The scientific novelty lies in substantiating the transformation of analytical skills from tools of purely informational processing into mechanisms for verification, interpretation, and strategic management of complex, often opaque AI algorithms. The presented material will be of interest to academic researchers and heads of financial departments, as well as practitioners – accountants, auditors, and financial planning specialists – and educational institutions developing modern curricula.

Keywords: *Artificial Intelligence, Financial Systems, Analytical Skills, Transformation of Professions, Critical Thinking, Data Analysis, Explainable AI (XAI), Risk Management, Financial Analysis, Human-Machine Interaction.*

INTRODUCTION

The rapid evolution and implementation of artificial intelligence systems in the financial sector are shaping a qualitatively new stage of development comparable in significance to previous industrial revolutions. AI-based solutions no longer exist merely in theory; they are tightly integrated into accounting, auditing, financial forecasting and risk management processes. In 2021 the global artificial intelligence market in financial technology was valued at 9,45 billion US dollars, and by 2030, according to forecasts, it will reach 41,16 billion US dollars at a compound annual growth rate (CAGR) 16,5 % in the period from 2022 to 2030. Fintech, or financial technology, is the application of modern technologies in the financial services sector to improve or automate banking and investment activities [1]. This dynamic indicates not simply a temporary trend but a fundamental restructuring of the entire industry.

The automation of routine operations — data entry, report reconciliation, preparation of standard reporting forms — frees specialists from mechanical work while simultaneously bringing to the forefront questions of rethinking their functions and required competencies. The relevance of the study is determined by the gap between the high speed of technological adaptation and the inertia in updating professional skills. Existing scientific literature typically focuses either on technical aspects (algorithmic models, platform solutions) or on macroeconomic effects of automation (employment reduction). However, little attention is paid to micro-level changes in analytical capabilities, which are becoming key for effective human – machine interaction.

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The author's hypothesis is that in the new human – AI ecosystem the value of a professional is determined not by computational speed but by the ability to formulate precise questions, critically evaluate AI-generated conclusions, and integrate them into a broad strategic and ethical context.

MATERIALS AND METHODS

In the last decade analytical skills have been regarded as a key component of effective interaction between specialists and smart financial systems. Recent studies demonstrate a growing market for AI implementation in the financial sector: according to Grand View Research, the AI market in fintech will reach substantial values by 2030, necessitating the enhancement of personnel's analytical competencies [1]. Gartner analysts note that although more than half of organizations initially planned to reduce their customer support staff with AI, by mid-2025 approximately 50% of them abandoned these plans due to underdeveloped analytical processes and the human factor in management [8].

Systematic literature reviews emphasize that accounting and auditing combine several methodological approaches. Hasan A. R. [4] analyzes the evolution of machine learning methods and expert systems in auditing, highlighting paradigms of statistical analysis and hybrid models, in which specialists' analytical skills determine the quality of algorithmic result interpretation. Meryem A., Said E. L. M. [5] distinguish three classes of research: optimization tasks, flexible risk-calculation models, and decision-making quality case studies, noting a lack of empirical data on the development of soft analytical skills among analysts. Kureljusic M., Karger E. [3] focus on predictive models in financial accounting, recommending a combination of neural-network algorithms and traditional time-series methods—an approach that requires from specialists deep proficiency in both statistical techniques and AI model result interpretation.

Applied research predominantly features industry cases addressing fraud detection and credit risk assessment. Ikhsan W. M. et al. [2] demonstrate how integrating advanced analytics with AI tools increases the accuracy of fraudulent transaction detection, yet emphasize that without developed data-handling skills specialists risk misinterpreting false positive signals. Mhlanga D.[6], in a study on machine learning for creditworthiness assessment in emerging economies, highlights the critical role of data preparation and cleaning skills, which are often underestimated in local contexts.

An important issue remains algorithmic bias and its impact on decision quality. Akter S. et al. [7] show that machine learning–based marketing models can reinforce existing prejudices if analysts lack competencies in identifying and correcting such distortions. Kupfer C. et al. [10] examine the phenomenon of automation bias in personnel selection, where weak analytical verification of AI recommendations leads to decreased managerial decision quality.

Finally, the study by Korzynski P. et al. [9] is devoted to generative AI (using ChatGPT as an example) as a new platform for management science, where analytical skills transform into the ability to formulate correct prompts (prompt engineering) and critically evaluate generated content.

Thus, the literature reveals a contradiction between the technological potential of AI systems and the level of users' analytical competencies: some studies highlight the advantages of hybrid models (statistics + AI), while others emphasize the need for in-depth personnel training. The least explored issues concern the integration of ethical principles into analyst education, methodologies for evaluating the ergonomics of human-machine interaction, and long-term monitoring of analytical decision effectiveness under rapidly changing financial market conditions.

RESULTS AND DISCUSSION

Results of the conducted study confirm the hypothesis that analytical skills do not lose their significance but undergo a profound transformation, becoming the cornerstone of the new financial ecosystem. The essence of this fundamental shift lies in the evolution of analytics from constructing calculations to reflective judgment. Whereas a finance specialist previously concentrated on collecting, processing and computing indicators within limited data sets, in an environment saturated with AI algorithms such operations are assumed by machines. Human intelligence thereby shifts to the meta level, being responsible for organizing and controlling the knowledge generation process.

This process includes several key directions, each of which lends analytical competencies a new meaning. First, there is the validation of AI-generated results: the specialist must demonstrate professional skepticism by verifying to what extent conclusions are logically justified, whether they are distorted by biased or incomplete data, and what assumptions are embedded in the algorithmic model. Overcoming automation bias — blind faith in the infallibility of the machine — requires precisely the business-context knowledge that the algorithm lacks [9, 10].

Second, the role of interpretation and explanation of results increases. Many modern models, especially deep neural networks, function as a black box, which creates serious challenges in regulated industries such as finance and auditing, where every decision must be documented and reproducible. Consequently, specialists proficient in Explainable AI (XAI) techniques become particularly sought after: they translate complex mathematical apparatus into language understandable to management, investors and regulators, and are capable of narrating the story behind the numbers, which becomes a crucial differentiator for financial leaders.

Finally, the third direction is strategic forecasting and scenario planning. AI indeed provides powerful predictive analytics tools, for example for modeling cash flows and identifying risks [7, 8]. However, algorithms rely exclusively on historical data. Human analysis must complement machine forecasts with qualitative judgments about future events not reflected in the past: new legislative initiatives, technological breakthroughs by competitors, shifts in consumer behaviour. In this context the analyst uses algorithmic outputs as a starting point for what-if scenario analysis and the development of preventive strategies.

To illustrate the described transformation of professional competencies a corresponding conceptual scheme has been developed (Figure 1).

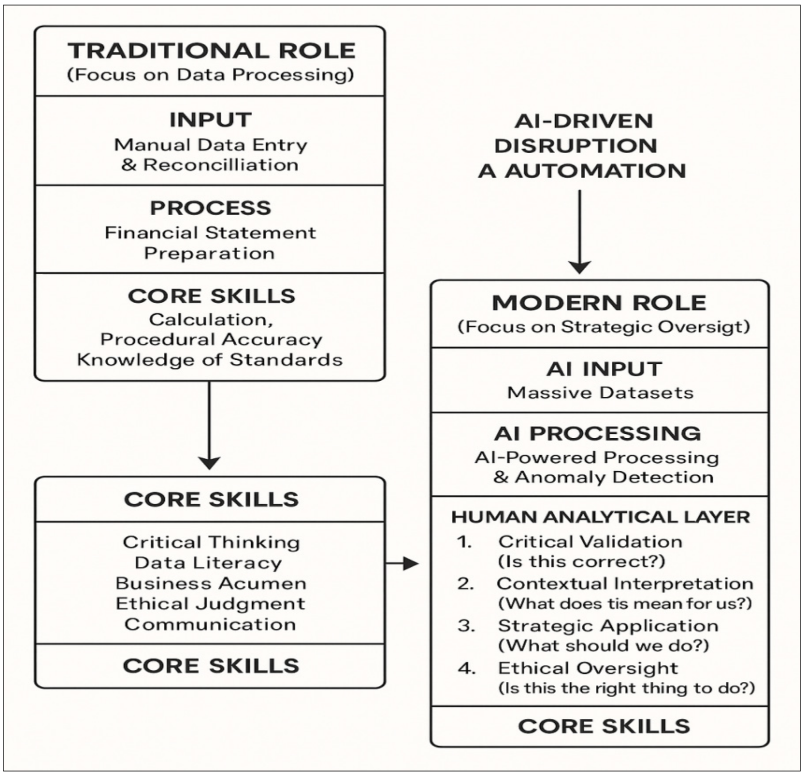

Fig.1. The Transformation of the Financial Professional's Role in the AI Era [2, 3, 7, 8]

This scheme demonstrates how automation of elementary, low-level operations frees the specialist to address higher-order tasks. At its center is the human analytical layer — a filter and amplifier for the conclusions generated by AI algorithms.

A crucial point here is synergy rather than rivalry. AI exceeds human capability in processing vast volumes of structured data, uncovering hidden patterns and performing large-scale computations at speeds unattainable by humans. At the same time, only a human can account for unformalized contexts, ethical dilemmas and long-term strategic perspectives. In this sense it is fair to state that AI can process data but only a human can bring wisdom. Under this wisdom is understood the totality of finely developed analytical skills applied to a specific situation. For a more detailed understanding of the evolution of specific skills, a comparative table can be presented (Table 1).

Table 1. Comparison of traditional and AI-oriented analytical skills in the financial sphere [3, 4, 10]

Category of Skill	Traditional Approach (Pre-AI Era)	AI-Oriented Approach
Data handling	Manual data collection, entry, cleaning of limited datasets.	Tasking AI systems with collection and processing of big data (Big Data), assessment of data quality and architecture.
Analysis and computation	Calculation of financial ratios, building financial models in Excel.	Interpretation of results from complex AI predictive models, understanding their assumptions and limitations.
Audit and control	Selective verification of transactions, document reconciliation.	Analysis of anomalies and outliers identified by AI across 100% of the data population; investigation of root causes.
Decision making	Based on historical data and personal experience.	Based on synthesis of data from multiple sources, AI forecasts, and qualitative human judgment.
Risk management	Reactive, based on analysis of past events.	Proactive, based on AI-driven predictive risk modeling and scenario analysis.
Communication	Preparation of standard reports, presentation of financial results.	Translation of complex AI findings into business language, data visualization, defence of AI-based decisions.

This scheme demonstrates how automation of elementary, low-level operations frees the specialist to address higher-order tasks. At its center lies the human analytical layer — a filter and amplifier for conclusions generated by AI algorithms. The essential point here is synergy rather than rivalry. AI surpasses humans in processing vast volumes of structured data, uncovering hidden patterns and and performing large-scale computations at speeds unattainable by humans. At the same time, only a human can account for unformalized contexts, ethical dilemmas and long-term strategic perspectives. In this sense it is appropriate to assert that AI can process data but only a human can bring wisdom. This wisdom denotes the totality of finely developed analytical skills applied to a specific situation. For a more detailed understanding of the evolution of specific skills one can present a comparative table (Table 1).

Table 1 illustrates not the disappearance of existing skills but their transformation and enrichment with new content. For example, the auditing skill does not vanish but shifts from routine verification to highly intellectual investigation of anomalies that AI effectively detects. To implement the proposed principles in practice, a specialized human-machine interaction framework in financial analysis has been developed. This model emphasizes the critical significance of the human analytical layer at every stage — from preliminary problem formulation and validation of machine outputs to interpretation of results and strategic scenario planning (Figure 2).

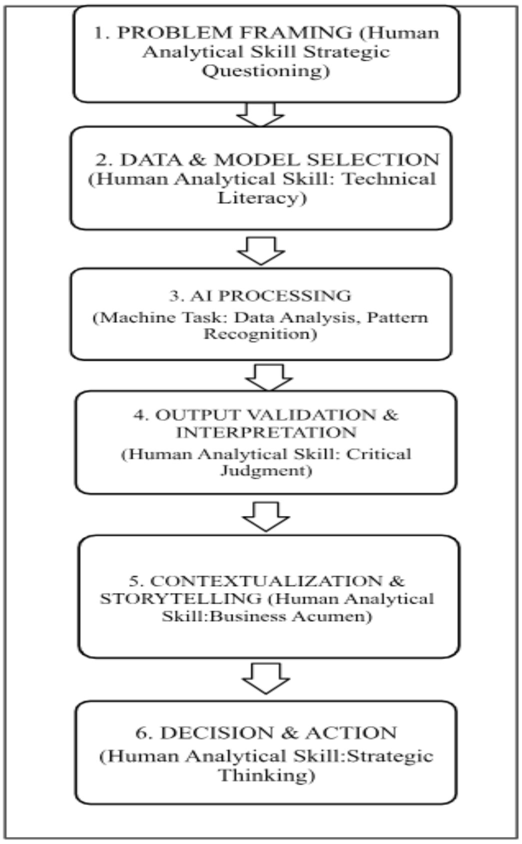

Fig.2. Framework for Human-AI Synergy in Financial Analysis [3, 5, 6]

This conceptual framework emphasizes that at stage 3 — data processing — artificial intelligence demonstrates itself as an exceptionally efficient tool, whereas at stages 1, 2, 4, 5, and 6 the key role is played by human analytical capabilities. It is the specialist who formulates the problem, selects the relevant data sources, constructs the methodology for interpreting the obtained results, and makes the final decision.

Thus, the integration of AI into financial systems does not diminish the value of human intelligence; on the contrary, it significantly raises the requirements for its quality. The very essence of the financial expert's contribution is redefined: AI is now determined not by the volumes of data [3] "run through" by algorithms, but by the depth of analytical understanding and the soundness of the conclusions drawn. Under these conditions, mastery of critical evaluation, contextual interpretation, and strategic thinking becomes the only adequate response to the challenges and opportunities of the new technological era.

CONCLUSION

The analysis conducted has enabled a broad examination of the transformation of the role of analytical competencies in the era of ubiquitous AI integration into the financial sector. As a result of the study, a paradigmatic shift has been identified: analytics, originally an instrument for automated computation, transforms into an instrument for formulating well-founded judgments; moreover, the automation of routine processes does not neutralize but rather expands the human role, demanding mastery of meta-level skills — validation of initial data, assessment of black box risks and ensuring ethical control. A set of analytical competencies oriented towards working with AI has also been established: professional skepticism towards machine outputs, the ability to decode and interpret complex models, strategic thinking for integrating qualitative assessments with machine forecasts and communicative ability to translate technical insights into the language of business practice. In addition, conceptual schemes of human–AI synergy are proposed, demonstrating the complementary and controlling function of human intelligence in relation to the computational capabilities of systems

Prospects for further research lie in the empirical investigation of the cognitive aspects of decision-making in the human–AI environment and in the development of specialized methodologies and training programs for the targeted development of the aforementioned analytical competencies

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