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AI-BASED DECISION SUPPORT FOR ASSET ALLOCATION MANAGEMENT AS A COMPONENT OF BUSINESS MODELS UNDER MARKET UNCERTAINTY



ABSTRACT

Purpose: *The aim of the study was to identify and evaluate the possibilities of using artificial intelligence assistants to support decision-making processes related to asset allocation, treated as an important component of the business model of an enterprise operating under conditions of market uncertainty.*

Methods: *The study was conducted on the example of three companies from the construction sector listed on the Warsaw Stock Exchange: Budimex S.A., Polimex Mostostal S.A., and Mirbud S.A. The analysis covered the years 2020–2024 and was based on two groups of data: annual fundamental indicators and daily closing stock prices. In the fundamental part, return on equity, debt ratio, asset utilization ratio, and the Altman discriminant model were used to construct a synthetic fundamental index. In the market part, daily logarithmic rates of return and the Sharpe ratio were calculated.*

Results: *The results indicate that AI assistants can effectively support the analytical process by accelerating calculations and increasing the repeatability of the procedure. At the same time, differences in model performance were observed, indicating the risk of errors in data interpretation.*

Discussion: *The study demonstrates that AI can be a useful tool supporting asset allocation management; however, its effectiveness depends on data quality, the precision of the analytical procedure, and human supervision. The findings highlight the importance of control mechanisms and model triangulation in AI-supported decision-making processes.*

KEYWORDS: *asset allocation management, business model, artificial intelligence, decision support, market uncertainty*

INTRODUCTION

Contemporary enterprises operate under conditions of increasing environmental volatility, including business cycle fluctuations, cost pressure, supply chain disruptions, complex geopolitical tensions, armed conflicts, and unpredictable capital market dynamics. Under such conditions, asset allocation management cannot be understood solely as a technical financial problem but should be treated as an important component of the business model. The business model defines how value is created, delivered, and captured and, consequently, the logic of resource allocation, utilization, and reconfiguration in response to environmental change (Teece, 2010, pp. 172-194). Therefore, the study of asset allocation under market uncertainty is important not only for corporate financial management practice but also for management sciences,

as it concerns the relationships between resources, strategic decisions, and the sustainability of the business model (Zott and Amit, 2010, pp. 216-226; Dyduch et al., 2021; Krzakiewicz and Cyfert, 2014, pp. 124-135).

The relevance of this research problem results from two co-occurring phenomena. First, market uncertainty increasingly affects decisions regarding both the structure of assets and their use. Recent studies show that uncertainty influences not only classical investment choices but also the allocation of new categories of resources, such as data assets, which are becoming a source of value in the digital economy (Chen et al., 2025; Such-Pyrgiel, 2020, pp. 447-462). This implies that contemporary asset allocation encompasses tangible and financial assets as well as intangible, informational, and technological assets, which are increasingly linked to the architecture of the business model. At the same time, the literature indicates that AI can support uncertainty management in typical decision situations but has limitations in rare, extreme, and weakly structured cases, which makes this area particularly important from a research perspective (Scholes, 2025).

Second, the rapid development of AI assistants is changing the very architecture of decision-making processes in enterprises. An increasing number of studies indicate that artificial intelligence is no longer merely a tool for automating individual operations but has become an element supporting managerial, strategic, and analytical decisions (Trunk et al., 2020, pp. 875-919). The most promising applications of AI concern decisions made under conditions of uncertainty, where the key issue is not full automation but the proper integration of human competences and AI systems (Trunk et al., 2020, 875-919). The effectiveness of the human–AI arrangement depends on an appropriate distribution of roles, responsibilities, and control mechanisms (Puranam, 2021, pp. 75-80). Consequently, the use of AI assistants in asset allocation management becomes not only a new tool of management practice but also an important subject of research on the organization of decision-making processes.

The relevance of this issue is further increased by the fact that the literature on the impact of AI on business models is developing dynamically yet remains fragmented. Recent systematic reviews show that AI increasingly influences the logic of value creation, business model design, and organizational processes. However, there is still a lack of empirical studies explaining how AI

technologies specifically reshape resource allocation and asset allocation decisions under uncertainty (Jorzik et al., 2024; Jobstreibitzer et al., 2025, pp. 372-396; Chrzanowska et al., 2024, pp. 429-442). Moreover, research on business model innovation through AI adoption indicates that implementing this technology requires changes in organizational structures, competencies, and managerial practices and thus concerns the core of the business model rather than only its operational layer (Roy et al., 2025, pp. 546-559). This means that the question of using AI assistants in asset allocation management simultaneously concerns decision-making efficiency, business model resilience, and organizational transformation.

The importance of the research problem also has a methodological dimension. In management and investment practice, AI assistants are increasingly used for data analysis, ranking construction, generating recommendations, and supporting decisions, yet the reliability of their outputs still requires critical evaluation. Discrepancies between models, sensitivity to input data formats, interpretative errors, and limited robustness to non-standard cases make research on their actual usefulness particularly necessary (Scholes, 2025; Trunk et al., 2020, pp. 875-919). From the perspective of management sciences, this implies the need to examine how AI affects decision quality, the speed of analysis, the transparency of procedures, and the replicability of results.

For these reasons, the present study formulates the following research question: to what extent does the application of artificial intelligence assistants improve and enhance the reliability of decision-making processes related to asset allocation treated as a component of the business model of enterprises operating under conditions of market uncertainty? Consequently, the objective of the study was defined as the identification and evaluation of the possibilities of applying artificial intelligence assistants to support decision-making processes concerning asset allocation, treated as an important component of the business model of enterprises operating under market uncertainty. Research on asset allocation management as a component of the business model in such conditions, conducted with the use of AI assistants, should be considered an important and current research problem (Teece, 2010, pp. 172-194; Jorzik et al., 2024; Roy et al., 2025, pp. 546-559). It combines several key areas of contemporary management sciences: business model theory, strategic

management under uncertainty, the use of data and intangible assets, and the development of AI-based decision support systems. Its practical significance results from the need to improve allocation decisions and enhance organizational resilience, while its theoretical significance stems from the necessity to explain how AI changes the logic of resource management and what role it plays in the reconfiguration of the business model in a turbulent environment (Grądzki, 2023, pp. 459-476).

RESEARCH METHODOLOGY

The study adopts a quantitative, comparative, and replicable methodology aimed at identifying and evaluating the possibilities of using AI assistants to support decision-making processes related to asset allocation, treated as an important component of the business model under market uncertainty. The procedure consists in selecting the best company for asset allocation within an investment portfolio while simultaneously verifying whether this analytical procedure can be reliably supported by AI assistants. The analysis covered three construction companies listed on the Warsaw Stock Exchange: Budimex S.A., Polimex Mostostal S.A., and Mirbud S.A., over 2020–2024, which ensured sectoral comparability and enabled the assessment of differences in efficiency, risk, and financial condition in a relatively homogeneous environment. The overall logic of the study combines business model, financial performance, and market behaviour perspectives, in line with the literature emphasising that allocation decisions should be analysed both from the standpoint of firm fundamentals and the risk-return relationship observed in capital markets (Teece, 2010, pp. 172-194; Zott and Amit, 2010, pp. 216-226; Sharpe, 1994, pp. 49-58; Sharpe, 2006).

The empirical basis comprised two complementary datasets: annual fundamental data (ROE, debt ratio, asset utilisation, Altman discriminant model) and daily closing stock prices. Both the researcher and the AI agents received only raw data in CSV format, without pre-calculated indicators, which increased transparency and ensured that all final results were derived from the same empirical material following an identical sequence of computational steps.

The first block of analysis concerned the risk-return relationship and was based on daily logarithmic rates of return. For each company, the average

daily return and the standard deviation of returns (volatility) were calculated and annualised assuming 252 trading sessions per year, and the Sharpe ratio, defined as the ratio of average return to standard deviation, was used to assess investment performance. The risk-free rate was deliberately omitted because all companies came from the same market and sector and the study had a relative, comparative character rather than aiming at an absolute evaluation against a risk-free asset (Sharpe, 1994, pp. 49-58; Sharpe, 2006). The second block addressed the fundamental assessment of the companies. A synthetic fundamental index was constructed by aggregating four indicators reflecting different dimensions of the firm's condition: ROE (profitability), debt ratio (financial risk), AU (operational efficiency), and the Altman model (insolvency risk), whose use is well established in the literature (Altman, 2013, pp. 430-435). To aggregate indicators expressed on different scales, min-max normalisation to the [0;1] range was applied, using the standard transformation for stimulants (ROE, AU, Altman model) and an inverse formula for the destimulant (debt ratio), so that higher debt reduced the final score. This approach offers interpretative simplicity and a common scale, although composite-indicator literature notes that results may be sensitive to extreme values and the choice of boundaries. The fundamental index was calculated as the arithmetic mean of the four normalised indicators with equal weights, a commonly used but simplifying assumption when strong theoretical grounds for differentiated weights are lacking (Greco et al., 2019, pp. 61-94; Becker et al., 2017, pp. 12-22).

The selection procedure for the best company was two-stage. In the first stage, companies were ranked according to the Sharpe ratio, and in the second stage according to the fundamental index. If the winner of both rankings was the same, this company was considered the best investment choice. Otherwise, a combined rule assigning a weight of 0.6 to the normalised Sharpe ratio and 0.4 to the fundamental index was applied, giving greater importance to the current risk-return relationship while preserving the influence of long-term financial condition. Methodologically, this constitutes a simplified multicriteria decision model in which input data are processed analytically and integrated into a decision procedure, while AI assistants automate calculations, standardise the procedure, and generate recommendations in line with predefined rules (Power, 2002; Shrestha et al., 2019, pp. 66-83).

An important element of the research design was the triangulation of AI agents. Three independent systems: Gemini, Claude, and ChatGPT received the same raw data and an identical, strictly specified prompt containing calculation formulas, the expected output format, and quality control rules, without access to intermediate results. This can be interpreted as methodological and source triangulation aimed at increasing reliability and replicability through the comparison of outputs generated independently from the same input data. In the literature, triangulation is described as a means of strengthening the validity of inference, while research on AI in management stresses the value of combining algorithmic analysis with human oversight and verification procedures (Carter et al., 2014, pp. 545-547; Trunk et al., 2020, pp. 875-919; Raisch and Krakowski, 2021, pp. 192-210).

The methodology is therefore appropriate for the research objective: it combines high-frequency market data with annual fundamental data, uses transparent and widely recognised tools (logarithmic returns, Sharpe ratio, Altman model, min-max-based synthetic index), allows full replication of all calculation stages, and, by embedding AI agents in a closed and formalised task environment, enables the assessment of their usefulness in supporting financial analysis and asset allocation decisions. At the same time, the small sample (three companies from one sector) constrains generalisability, equal weights in the fundamental index simplify economic relationships and may affect rankings, the Sharpe ratio reflects historical relationships, and AI agents can introduce calculation and interpretation errors even under strict prompting, which means that researcher oversight remains necessary and the study should be treated as an exploratory assessment of AI usefulness in controlled decision-making conditions (Becker et al., 2017, pp. 12-22; Kelemen et al., 2024; Trunk et al., 2020, pp. 875-919).

THE ROLE AND FUNCTIONS OF ASSET ALLOCATION MANAGEMENT IN STRENGTHENING THE RESILIENCE OF THE BUSINESS MODEL UNDER CONDITIONS OF MARKET UNCERTAINTY

Under increasing market uncertainty, asset allocation management should be understood not only as a financial function but as an important component of the enterprise's business model. The business model enables the understanding of the logic of operation and the intentional modification of its components and architecture to create new logics of value creation, delivery, and capture (Andreini et al., 2022; Foss and Saebi, 2017, pp. 200-227). In this perspective, asset allocation is not a mere technical division of resources into fixed and current assets but a set of strategic decisions on which resources to maintain, develop, protect, or reconfigure to preserve the firm's ability to create value despite changing environmental conditions (Teece, 2010, pp. 172-194; Zott and Amit, 2010, pp. 216-226; Casadesus-Masanell and Ricart, 2010, pp. 195-215). The durability of the business model depends therefore less on the static efficiency of assets and more on their flexibility and transformability.

As market uncertainty rises and the predictability of demand, financing costs, investment values, supply chain stability, and competitors' behaviour decreases, assets cease to be only carriers of current productivity and become instruments of stabilisation, adaptation, and strategic optionality. From a business model perspective, what matters is not only the volume of assets but also their structure, liquidity, reversibility, modularity, and potential for reuse in new configurations of activities. The ability to reconfigure assets is a fundamental condition for maintaining competitive advantage in a turbulent environment (Haarhaus and Lienen, 2020; Herhausen et al., 2021, pp. 435-455), which means that asset allocation management functions as a mechanism integrating the business model with the requirements of an uncertain environment.

One core function of asset allocation as an element of the business model is to protect liquidity and ensure the continuity of operations in the face of shocks, which corresponds to its stabilising role. Research on corporate finance shows that financial flexibility, understood as the ability to maintain liquidity reserves and unused debt capacity, increases investment capabilities and resilience to changing

conditions, while higher uncertainty often leads firms to increase liquid assets as a rational form of protection and preservation of investment options (Marchica and Mura, 2010, pp. 1339-1365; Chortareas and Noikokyris, 2021, pp. 25-35; Goodell et al., 2021). At the same time, asset allocation fulfils an adaptive and developmental function: by allocating part of the assets to resources that can be quickly shifted or reconfigured, enterprises build strategic flexibility and support product and business model innovation, especially in knowledge and technology-based domains (Herhausen et al., 2021, pp. 435-455; Zhou and Wu, 2010, pp. 547-561; Schneckenberg et al., 2016, pp. 404-419; Dyduch et al., 2021).

Based on the literature, asset allocation management, treated as a component of the business model, can thus be seen as performing four interrelated roles under conditions of market uncertainty: stabilising the enterprise through liquidity and safety buffers, enhancing adaptability by enabling resource reconfiguration, supporting development by directing assets towards future growth options, and enabling business model transformation when the existing logic of value creation no longer fits environmental conditions. The quality of asset allocation management therefore co-determines the resilience, durability, and strategic effectiveness of the enterprise and should be viewed not merely as a financial issue, but as a central problem of strategic management concerning the relationships between resources, uncertainty, and the organisation's long-term ability to create value (Teece, 2010, pp. 172-194; Casadesus-Masanell and Ricart, 2010, pp. 195-215; Haarhaus and Liening, 2020).

THE USE OF AI ASSISTANTS IN ASSET ALLOCATION MANAGEMENT UNDER CONDITIONS OF UNCERTAINTY

Contemporary enterprises operate under increasing volatility and market uncertainty, while the business model determines how an organisation creates, delivers, and captures value (Osterwalder and Pigneur, 2013, pp. 237-244). Decisions on which assets to maintain, develop, protect, digitalise, or share with partners directly affect the durability and adaptability of the business model (Teece, 2010, pp. 172-194; Zott and Amit, 2010, pp. 216-226; Czakon, 2012, pp. 25-35), and under such conditions asset allocation decisions become

complex and consequential, as they must account for volatility in demand, financing, and strategic outcomes.

In this context, the use of AI assistants makes asset allocation management an even more important management tool. AI assistants increase the capacity to process large data volumes, detect patterns, compare scenarios, and rapidly generate recommendations regarding resource use, supporting the evaluation of investment profitability, project prioritisation, risk analysis, liquidity planning, simulation of allocation variants, and the identification of weak environmental signals. However, research on organisational decision-making shows that the greatest value of AI lies not in replacing managers but in complementing algorithmic analysis with human interpretation, intuition, and contextual understanding (Jarrahi, 2018, pp. 577-586; Trunk et al., 2020, pp. 875-919). AI assistants can therefore improve allocation decisions only when embedded in appropriate decision-making structures, standards of accountability, and verification procedures.

The incorporation of AI assistants into asset allocation management is simultaneously a consequence of ongoing transformations in business models. Studies show that AI implementation does not merely improve isolated processes but affects the logic of value creation, cost structures, data usage, employee roles, and decision-making architectures (Jobstreibizer et al., 2025, pp. 372-396). Literature reviews indicate that AI increasingly influences business models, yet the research field remains fragmented and many relationships between AI, resources, decisions, and firm performance require further clarification (Jorzik et al., 2024). At the same time, AI adoption supports business model innovation but requires parallel organisational and competence-related changes, confirming that it is not only a technological implementation but also a transformation of asset and capability management (Roy et al., 2025, pp. 546-559). Consequently, AI-supported asset allocation simultaneously strengthens information processing and adaptive capacity and improves the alignment between the asset structure and the business model logic, while at the same time introducing risks such as model bias, over-automation and weakened managerial accountability (Herhausen et al., 2021, pp. 435-455; Haarhaus and Liening, 2020; Doshi et al., 2025, pp. 583-610; Trunk et al., 2020, pp. 875-919).

From a research perspective, the problem is relevant because it links business model theory, strategic management under uncertainty, dynamic capabilities, resource management, and human–AI decision-making. Recent reviews show that research on AI in business models and managerial decision-making remains fragmented, with conceptual and review work dominating, while in-depth studies on how AI changes the architecture of asset allocation decisions, the organisational mechanisms that determine the effectiveness of such solutions, and their impact on resilience and performance are still scarce (Jorzik et al., 2024; Jobstreibizer et al., 2025, pp. 372-396; Trunk et al., 2020, pp. 875-919). Asset allocation management using AI assistants should therefore be seen both as an important management tool and as a significant research problem, whose practical importance stems from its impact on resilience, liquidity, adaptive capacity, and strategic decision quality, and whose scientific significance arises from the need to explain how AI reshapes resource use, human–algorithm relations, and the structure of the business model under persistent uncertainty.

RESULTS

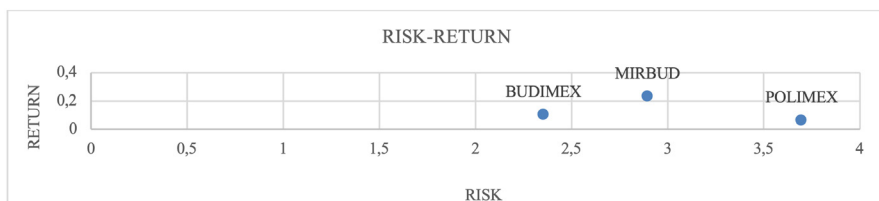
The first stage of the analysis assessed the risk-return relationship based on daily logarithmic rates of return calculated from closing stock prices and annualised under the assumption of 252 trading sessions per year. The resulting risk-return characteristics and Sharpe ratios for each company are presented in Table 1. MIRBUD achieved the highest Sharpe ratio (1.055), indicating the most favourable risk-return profile in the analysed period, while BUDIMEX, with a Sharpe ratio of 0.522, occupied the second position, reflecting a moderately favourable relationship between return and risk. POLIMEX recorded a negative annual return combined with the highest volatility, which translated into a negative Sharpe ratio and low investment attractiveness from the perspective of the historical risk-return relationship.

Table 1. Risk–return characteristics and Sharpe ratio for the analysed companies

Company	μ annual	σ annual	Sharpe
MIRBUD	0,4808	0,4557	1,055
BUDIMEX	0,1942	0,3722	0,522
POLIMEX	-0,0016	0,5676	-0,003

Source: own elaboration.

As shown in Figure 1, the position of each company in the risk–return space confirms the numerical results, clearly distinguishing MIRBUD as the entity with the most favourable combination of return and volatility.

Figure 1. Risk–return matrix for the analysed companies

Source: own elaboration.

The second stage of the analysis evaluated the financial condition of the enterprises using a synthetic fundamental index constructed from average values of return on equity, debt ratio, asset utilisation, and the Altman discriminant model over the study period. The resulting index values are presented in Table 2. MIRBUD obtained the highest index value (0.828), resulting from very high efficiency in asset utilisation, a favourable debt assessment after normalisation, and the strongest Altman score, which indicates the most balanced economic and financial profile among the analysed firms. BUDIMEX placed second, despite recording the highest ROE, its overall position was weakened by a less favourable debt assessment and lower values of the remaining components, whereas POLIMEX had the lowest index value due mainly to low asset utilisation efficiency and a weak Altman evaluation.

Table 2. *Fundamental index of the analysed companies based on normalised financial indicators*

Company	ROE	DEBT	AU	ALTMAN	INDEX
MIRBUD	0,398	0,916	1,000	1,000	0,828
BUDIMEX	1,000	0,000	0,074	0,151	0,306
POLIMEX	0,000	1,000	0,000	0,000	0,250

Source: own elaboration.

The rankings based on the Sharpe ratio and the fundamental index were fully consistent: MIRBUD ranked first, BUDIMEX second, and POLIMEX third in both perspectives. This convergence of market-based and fundamental results strengthens the conclusion that MIRBUD was the most attractive company for asset allocation in an investment portfolio during the analysed period and indicates that, from a decision-support perspective, both analytical layers lead to a consistent recommendation, which increases the reliability of the model in an AI-supported environment.

The comparison of company rankings based on the Sharpe ratio and the fundamental index showed full consistency of results which in both cases MIRBUD was ranked first, BUDIMEX second, and POLIMEX third. This convergence of market-based and fundamental perspectives strengthens the conclusion that MIRBUD was the most attractive company for asset allocation in an investment portfolio during the analysed period. From a decision-support perspective, it means that both the risk-return layer and the fundamental layer lead to a consistent recommendation, increasing the reliability of the model and its potential for application in an AI-supported environment.

The final stage of the study attempted to automate the analytical process using three AI agents: Gemini 3.1 Pro, Claude Sonnet 4.6, and ChatGPT-5.2. Each model received only raw financial and market data and an identical prompt defining the calculation procedure and the expected output format. The numerical results generated by Gemini 3.1 Pro are summarised in Table 3, while the corresponding outputs from Claude Sonnet 4.6 are presented in Table 4.

Table 3. *Results of the Gemini 3.1 Pro analysis*

Company	mu_d		sigma_d		mu_annual	sigma_annual		Sharpe	
MIRBUD	0,001908		0,028705		0,480780	0,455674		1,055096	
BUDIMEX	0,000771		0,023448		0,194181	0,372217		0,521688	
POLIMEX	-0,000006		0,035754		-0,001609	0,567573		-0,002835	
Company	RO E_avg	ZAD_avg	AU_avg	ALT_avg	RO E_norm	ZAD_norm	AU_norm	ALT_norm	Index
MIRBUD	0,1760	0,6620	1,3449	6,7064	0,3977	0,9158	1,0000	1,0000	0,8284
BUDIMEX	0,5218	0,8232	1,1537	4,9584	1,0000	0,0000	0,0736	0,1507	0,3061
POLIMEX	-0,523	0,6472	1,1385	4,6482	0,0000	1,0000	0,0000	0,0000	0,2500

Source: own elaboration based on AI-generated output.

The results produced by Gemini 3.1 Pro and Claude Sonnet 4.6 were consistent with the manually conducted analysis, both in terms of indicator values and the final ranking of companies. Both models indicated MIRBUD as the best investment choice. In contrast, ChatGPT-5.2 generated an incorrect recommendation in favour of POLIMEX as a result of errors in the interpretation and reading of input data.

Table 4. *Results of the Claude Sonnet 4.6 analysis*

Company	Sharpe_norm	Fund_index	Combined_score
MIRBUD	1,0000	0,8284	0,9314
BUDIMEX	0,4958	0,3061	0,4199
POLIMEX	0,0000	0,2500	0,1000

Source: own elaboration based on AI-generated output.

These findings suggest that AI agents can significantly improve the asset allocation analysis process, especially by automating calculations and processing input data, but they do not eliminate the risk of errors, particularly at the interpretation stage. For this reason, the triangulation of AI models appears justified, as it increases the reliability of results and reduces the risk

of accepting an incorrect investment recommendation. The convergence between manually obtained results and those generated by independent AI agents indicates high replicability of the procedure and confirms its potential for application in decision support systems.

DISCUSSION

The results indicate that MIRBUD was the most attractive entity for asset allocation in the analysed period, both from the capital market perspective and on the basis of fundamental analysis. Its advantage was determined by the highest Sharpe ratio and the dominant value of the synthetic fundamental index, which jointly suggests that allocation decisions should not rely solely on historical market prices or exclusively on financial statement data, but on an integrated approach to both dimensions. In this sense, the findings support the view that business models and allocation decisions should be analysed as a system of relationships between the logic of value creation, the structure of resources, and the enterprise's ability to sustain performance in a changing environment (Teece, 2010, pp. 172-194; Zott and Amit, 2010, pp. 216-226). From the perspective of decision support systems, the results confirm the usefulness of the proposed model, which integrates market and fundamental analysis within an AI-supported decision process.

The study contributes to the literature in three main ways. First, it demonstrates that integrating risk-return analysis with fundamental assessment can lead to consistent investment decisions, even in a limited sample, thereby offering a practical procedure for asset allocation management under uncertainty. Second, it provides an empirical example of applying AI assistants to a complete, replicable analytical procedure based solely on raw data, illustrating the complementary role of AI, which supports data processing and recommendation generation while humans retain control and interpretative functions (Trunk et al., 2020, pp. 875-919). Two models correctly replicated the manual procedure and indicated the same investment choice, whereas a third model made an error at the data reading stage, highlighting the limits of automation and confirming the need for human oversight. Third, the study shows that triangulation of AI agents can function as a practical validation

mechanism by convergence between the outputs of two independent models and the manual analysis increased confidence in the procedure, while the discrepancy from the third model revealed a potential source of error and suggests that reliability in AI-supported analysis should be sought through multi-model comparison rather than reliance on a single system.

The findings are also relevant for the literature on business models and market uncertainty, which links a firm's ability to create value with the organisation of resources, processes, and relationships with the environment. From an investor's perspective, asset allocation management should thus be understood not merely as the selection of the most profitable company but as the allocation of capital to entities that combine market efficiency with durable economic foundations, and the present analysis illustrates how business model theory can be operationalised in investment decisions with AI support, provided that the procedure remains transparent, replicable, and subject to control.

At the same time, the exploratory character of the study, the small sample of three companies from one sector, the use of an equal-weighted fundamental index, and the historical nature of the Sharpe ratio limit the generalisability of the findings and mean that the results should be treated as a premise for further research rather than a basis for universal conclusions (Sharpe, 1994, pp. 49-58; Sharpe, 2006).

CONCLUSION

The study aimed to identify and evaluate the possibilities of applying AI assistants to support decision-making processes related to asset allocation in enterprises operating under market uncertainty. Using a combined risk-return and fundamental perspective, the analysis of three construction companies listed on the Warsaw Stock Exchange in 2020-2024 indicated MIRBUD as the most attractive company, as it ranked first both in the Sharpe ratio and in the fundamental index.

The results show that, given a clearly defined analytical procedure, AI assistants can effectively support calculation and ranking processes, but do not eliminate the risk of errors and therefore require control and verification

of outputs. AI should be treated as an element of decision support rather than an autonomous decision-maker. For management practice, the study indicates that integrating risk-return analysis with fundamental assessment offers a more balanced basis for asset allocation decisions, while AI tools can automate parts of the analytical process and reduce workload, provided that appropriate control mechanisms including analyst verification and, where possible, triangulation of several models are applied.

From a theoretical perspective, the study confirms that asset allocation management can be understood as an important component of the business model, connecting market efficiency with assessments of economic resilience, and that multi-model triangulation constitutes a useful methodological solution for increasing the reliability and replicability of AI-supported analyses. In this way, the proposed approach offers a practical model for integrating classical financial measures with AI tools in asset selection under uncertainty and can serve as a starting point for more advanced AI-based decision support systems in this area.

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