Natalia PAWLAK[1], Agnieszka STACHOWIAK[2], Piotr WIECZOREK[3]

AI-SUPPORTED DECISION-MAKING IN PROCUREMENT: A CONCEPTUAL MODEL FOR SMART AND RESILIENT BUSINESS ENVIRONMENTS

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This paper addresses the integration of artificial intelligence (AI) with multi-criteria decision-making (MCDM) approaches in procurement under the conditions of high uncertainty characteristic of VUCA/BANI environments. Based on a structured literature review, a conceptual causal loop diagram (CLD) is developed to model the relationships between external factors, internal organizational conditions, and AI-supported decision-making capabilities. The results indicate that procurement decisions should be understood as a dynamic system influenced by interdependencies between variables such as supplier base availability, market volatility, and procurement maturity. The model identifies key drivers of cost, supply-chain resilience, and decision quality, highlighting the central role of highly connected variables. The study contributes to the field by proposing an integrated framework supporting the adoption of AI in procurement decision processes. The proposed model provides a foundation for further empirical research and may support organizations in the gradual implementation of data-driven approaches in procurement management. Future research should focus on human-centric AI, regulatory alignment, and continuous system improvement to ensure sustainable and effective adoption.

Keywords: causal loop diagram, AI, VUCA, BANI

[1] Poznan University of Technology, Faculty of Engineering Management. ORCID: 0000-0002-7453-4449.
[2] Poznan University of Technology, Faculty of Engineering Management. ORCID: 0000-0002-1874-9218.
[3] Beiersdorf AG, Vienna, Austria.

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1. INTRODUCTION

Today's business environments are characterized by a growing level of uncertainty, volatility, and complexity. The concepts of VUCA (Volatility, Uncertainty, Complexity, Ambiguity) and BANI (Brittle, Anxious, Nonlinear, Incomprehensible) have become widely used frameworks for describing the dynamic and unpredictable conditions under which modern organizations operate (Bennett, Lemoine, 2014; Cascio, 2020). Recent global events such as the COVID-19 pandemic, the war in Ukraine, tensions and military conflict in the Middle East including Iran, along with disruptions related to global energy markets and trade relations, have demonstrated how rapidly external conditions can change and how strongly they affect business decision-making processes.

These challenges have had a particularly powerful impact on supply chains and procurement processes. Organizations have been forced to react quickly to disruptions in logistics networks, shortages of critical materials, sudden price fluctuations, and regulatory changes. As a result, procurement decisions increasingly require the simultaneous consideration of multiple external and internal factors, including supplier availability, geopolitical conditions, regulatory requirements, technological constraints, and operational capabilities. The complexity of supplier evaluation (Godala, 2017) has long been recognized in procurement research, where multiple criteria must be balanced simultaneously to achieve optimal outcomes (Veldhuis et al., 2025).

At the same time, rapid advances in digital technologies – particularly artificial intelligence (AI), data mining, and business analytics – are transforming the way organizations approach decision-making. AI-based systems enable the processing of large volumes of data, identification of hidden patterns, and generation of predictive insights, thereby offering significant potential to enhance procurement effectiveness. However, despite these opportunities, the adoption of AI in procurement remains uneven. Organizations face challenges related not only to technological implementation, but also to data quality, organizational readiness, and integrating AI-generated insights into managerial decision processes (Allal-Chérif et al., 2021; Koch, Shafie, 2022).

Existing research typically addresses procurement decision-making from separate perspectives, focusing either on multi-criteria decision-making (MCDM) methods, artificial intelligence applications, or supply chain risk management. However, relatively limited attention has been given to integrated approaches that combine these perspectives within a single analytical framework, particularly in the context of highly dynamic and uncertain environments.

This paper addresses the following research question: How can artificial intelligence be integrated with multi-criteria decision-making approaches to support procurement decisions under conditions of high uncertainty in VUCA/BANI environments?

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To further structure the analysis, the following sub-questions are considered:

R1: What key factors influence procurement decision-making in uncertain environments?

R2: How can AI-based tools complement traditional MCDM methods?

R3: What organizational conditions enable effective AI-supported decision-making in procurement?

The purpose and the main contribution of this study is in developing a conceptual causal loop model that integrates multi-criteria decision-making logic, AI-supported analytical capabilities, and dynamic environmental risk factors. The proposed model provides a structured framework for understanding how these elements interact to influence procurement decision quality and supply chain resilience. In addition, the study highlights the limitations of AI-based systems, including their dependence on data availability and quality, challenges in assessing the reliability of information, and the risk of generating incorrect or misleading outputs. These constraints underline the importance of maintaining human oversight and critical evaluation in AI-supported decision-making processes. By offering an integrated perspective, this paper contributes to developing more adaptive and resilient procurement decision frameworks suitable for increasingly complex business environments.

2. MATERIALS AND METHODS

2.1. Research Design

This study adopts a conceptual research approach aimed at developing a theoretical model that explains the relationships between key factors influencing procurement decision-making in uncertain and dynamic environments.

The research is exploratory in nature and focuses on integrating existing knowledge from multiple research streams into a coherent analytical framework. The study combines a systematic literature analysis with conceptual modelling, using causal loop diagramming (CLD) (Weiss et al., 2025) to represent relationships between variables and feedback mechanisms within the system. Figure 1 summarizes the consecutive stages of the research process. The study began with identifying the research gap and formulating the research questions. Subsequently, a structured literature review was conducted to identify variables describing procurement decision-making, AI applications, and supply chain resilience. These variables were then categorized and integrated into a causal loop diagram, which was ultimately analyzed in terms of structural relationships and system connectivity.

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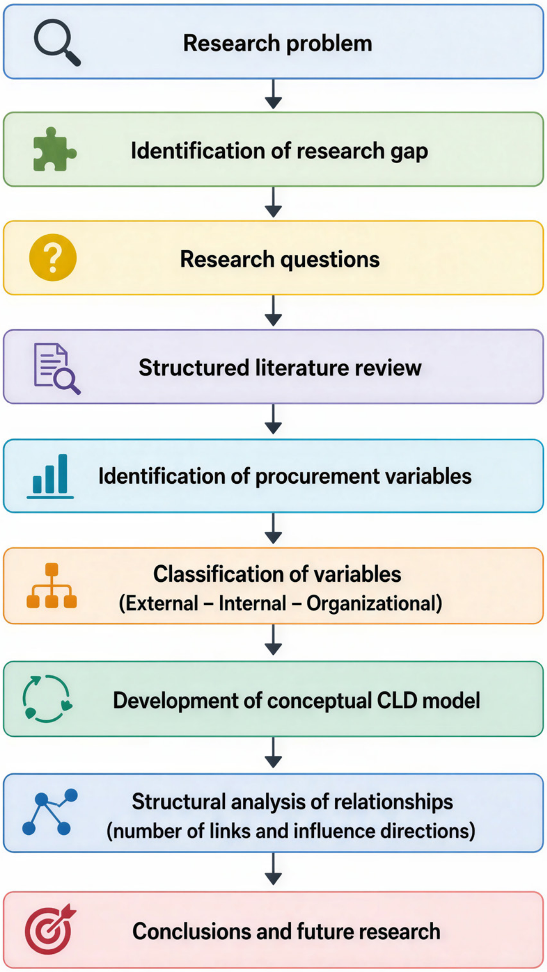

Fig. 1. Research methodology adopted in the study (own elaboration)

2.2. Literature Analysis

A literature review was conducted to identify key concepts, variables, and relationships relevant to procurement decision-making, artificial intelligence applications, and supply chain risk management.

The analysis focused on three primary research areas:

- multi-criteria decision-making (MCDM) methods in procurement,
- artificial intelligence and data analytics in decision support,
- supply chain risk, resilience, and uncertainty in VUCA/BANI environments.

The literature review followed a structured search and selection procedure aimed at identifying publications relevant to procurement decision-making, artificial

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intelligence, and supply chain resilience. Searches were conducted in the Scopus, Web of Science, and Google Scholar databases using combinations of keywords, including procurement, supplier selection, multi-criteria decision making, MCDM, artificial intelligence, machine learning, data mining, supply chain resilience, risk management, VUCA, and BANI.

The review primarily covered publications published between 2015 and 2025 in order to capture recent developments in AI-supported procurement, while seminal studies on MCDM and supplier selection were also included where necessary to provide theoretical foundations. Only peer-reviewed journal articles, conference papers, and recognized academic books written in English were considered. Publications were selected based on their relevance to the research objective, scientific impact, methodological quality, and contribution to one or more of the three research streams analyzed. Duplicates and publications not directly related to procurement decision support or AI applications were excluded. The final body of literature served as the basis for identifying variables and relationships incorporated into the conceptual model.

2.3. Model Development

Based on the literature analysis, key variables influencing procurement decision-making were identified and grouped into three categories:

- external factors, such as geopolitical stability, market conditions, and regulatory environment,
- internal organizational factors, including product characteristics, inventory capacity, and operational constraints,
- organizational and system factors, such as procurement maturity and AI-supported decision-making capabilities.

To represent the interactions among these variables, a causal loop diagram (CLD) was developed. This approach allows for the visualization of both direct and indirect relationships, as well as feedback loops that influence system behavior over time.

The model was constructed iteratively, ensuring logical consistency between variables and alignment with insights derived from the literature.

2.4. Analytical Approach

The developed conceptual model was analyzed using a structural approach focused on the relationships between variables. The analysis included:

- identification of the number of connections between variables,
- assessment of the direction of influence (positive or negative relationships),
- evaluation of the relative importance of variables based on their connectivity within the system.

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This approach enabled the identification of key drivers and central nodes that influence procurement decision-making processes, as well as the main outcome variables, including cost, supply chain resilience, and procurement decision quality.

2.5. Research Limitations

The study is conceptual in nature and does not include empirical validation of the proposed model. The relationships between variables are derived from the existing literature and theoretical assumptions.

As a result, the model should be treated as a framework for further investigation rather than a fully validated decision-support tool. Future research should focus on empirically testing the model using case studies, simulation methods, or quantitative data analysis to verify its applicability in real-world organizational contexts.

3. LITERATURE REVIEW

3.1. Decision-making processes in procurement

Procurement processes constitute one of the key elements of enterprise management, influencing both the level of operational costs and the efficiency of supply chain functioning. The literature emphasizes that supplier selection decisions belong to the most complex decision problems in operations management, as they require the simultaneous consideration of multiple criteria of different nature (Aissaoui et al., 2007; Baryannis et al., 2019; Bienhaus et al., 2018).

Early research in this area focused on identifying the fundamental criteria for supplier selection, such as price, quality, and delivery reliability (Veldhuis et al., 2025). Later studies highlighted the increasing importance of more complex factors, such as supplier flexibility, innovativeness, and the ability to cooperate in the long term.

The contemporary approach to procurement management assumes the need to consider a broader business context, including operational risk, supply chain disruptions, and changing geopolitical conditions (Gholizadeh et al., 2020). As a result, procurement decision-making processes require tools enabling systematic analysis of multiple criteria and large datasets.

3.2. Multi-Criteria Decision Making (MCDM) methods

One of the most frequently applied approaches to solving complex decision problems is the use of Multi-Criteria Decision Making (MCDM) methods (Pamučar et al., 2023). These methods enable the structuring of decision problems through the identification of criteria, assignment of weights, and evaluation of available decision alternatives (Mathebula et al., 2025).

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Among the most widely used MCDM methods are:

- AHP (Analytic Hierarchy Process) – a method developed by Saaty that enables hierarchical structuring of decision problems and evaluation of the relative importance of individual criteria (Weiss et al., 2025),
- TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) – a method based on selecting the solution closest to the ideal solution (Mathebula et al., 2025; Zouggari, Benyoucef, 2012),
- PROMETHEE – a method based on preference comparisons between decision alternatives (Dotoli et al., 2020).

MCDM methods are widely applied in supplier selection, bid evaluation, and supply chain risk assessment problems. Their main advantage is the ability to incorporate both quantitative and qualitative criteria.

At the same time, the literature indicates certain limitations of these methods, particularly the need to predefine the set of decision criteria and their weights. In practice, this means that the quality of the analytical results largely depends on the knowledge and experience of decision-makers.

3.3. Artificial intelligence and data mining in decision-making processes

The dynamic development of digital technologies has led to growing interest in the use of artificial intelligence in enterprise decision-making processes. AI and data mining methods enable the analysis of large datasets, identification of hidden patterns, and development of predictive models supporting decision-making (Kar, 2015).

The literature indicates that AI applications in procurement include, among others:

- supplier risk analysis and assessment,
- demand and market trend forecasting,
- supplier performance analysis,
- identification of price anomalies and potential fraud.

Research shows that AI-based systems can significantly increase the efficiency of procurement processes by automating routine tasks and providing more precise data analyses. In some cases, the application of AI can reduce procurement process execution time by up to a half while increasing the accuracy of supplier evaluation (Awan et al., 2021).

At the same time, the literature points to significant barriers to AI implementation in organizations, such as data integration challenges, lack of appropriate IT infrastructure, ethical issues, and limited organizational readiness (Weber et al., 1991).

3.4. Smart business environment

With the development of digital technologies, the concept of smart business environments has emerged, in which information systems, data analytics, and

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artificial intelligence technologies support decision-making processes in organizations (Vaezi et al., 2024).

In such environments, data originating from various sources, both internal and external, are integrated and analyzed in real time, thus enabling more flexible responses to market changes. In the context of procurement management, this means the possibility of continuously monitoring supplier markets, analyzing risks, and optimizing procurement decisions (Kamal et al., 2024).

The importance of cooperation between artificial intelligence systems and human decision-makers is increasingly emphasized. In this approach, AI serves as a tool supporting data analysis and generating recommendations, while final decisions remain the responsibility of managers responsible for procurement management (Mattiello et al., 2022).

3.5. Research gap

The literature analysis indicates that despite the growing interest in the use of artificial intelligence in procurement management, a significant research gap exists regarding the integration of different analytical approaches. Existing research typically focuses on selected, distinct research streams.

The first encompasses the application of multi-criteria decision support (MCDM) methods in supplier selection. Models based on methods such as AHP, TOPSIS, and VIKOR have been extensively developed in the literature, often augmented with fuzzy or hybrid approaches (Chai et al., 2020; Chai et al., 2013; Ho et al., 2010). Literature reviews indicate the growing complexity of decision models and the need to consider multiple, often conflicting, criteria in supplier evaluation.

The second stream of research focuses on the use of artificial intelligence and data analytics in supply chain management. In particular, the importance of big data and machine learning in improving forecast accuracy, process optimization, and increasing supply chain resilience to disruptions is emphasized (Dubey et al., 2019; Ivanov, Dolgui, 2020; Wamba et al., 2017). These studies indicate that the use of AI enables better processing of large data sets and decision-making under conditions of uncertainty.

The third area encompasses risk management in supply chains, particularly in the context of increasing volatility and unpredictability in the environment referred to as VUCA or BANI. The literature develops the concepts of resilience and adaptive capacity of supply chains, which are crucial in conditions of global disruption (Dolgui et al., 2020; Ivanov, 2020).

Despite significant achievements in each of these areas, relatively few studies propose integrated approaches combining MCDM methods, artificial intelligence, and data analytics within a single decision-making model. Existing reviews indicate the need for further research on integrating decision-making techniques and AI tools in the context of risk and uncertainty management (Baryannis et al., 2019; Fahimnia et al., 2015).

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In particular, there is a noticeable lack of comprehensive models that simultaneously consider the multi-criteria nature of purchasing decisions, the use of artificial intelligence and data mining tools, and the dynamic risk factors characteristic of VUCA/BANI environments. This gap points to the need to develop integrated decision-making frameworks that will enable more effective and adaptive management of purchasing processes under conditions of high uncertainty.

The development of such a model constitutes one of the main objectives of this article.

4. RESEARCH RESULTS

Based on the analysis, a conceptual causal loop diagram (CLD) was developed, which presents a set of selected criteria influencing the procurement decision-making process and the relationships between topics explained in table 1.

Table 1.Causal loop diagram – symbols used

Symbol	Description
	Group of external factors
	Group of internal factors
	Group of organizational\system factors
→	Connection of criteria with influence direction
⊕	Impact on criteria value –increase
⊖	Impact on criteria value – decrease
	Connections of criteria from various groups
	Connections of criteria within the same group
	Connections of criteria to the main characteristics

Source: own elaboration.

The diagram allows for the identification of both direct and indirect relationships between individual factors that, in practice, affect the functioning of procurement processes in enterprises (fig. 2).

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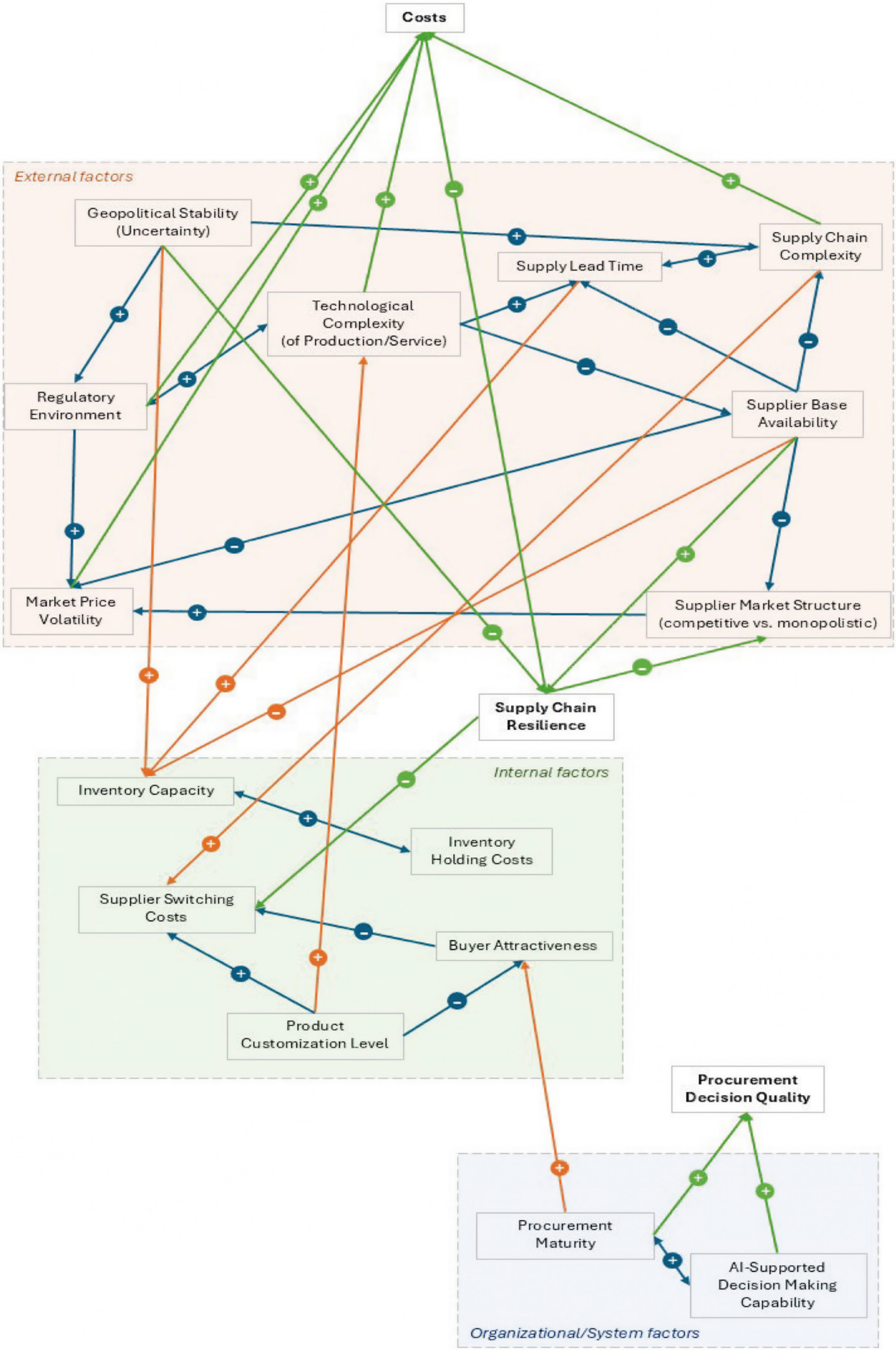

Fig. 2. Causal loop concept (own elaboration)

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The model integrates variables representing external conditions, internal organizational characteristics, and system-level capabilities, including AI-supported decision-making. The diagram captures both direct and indirect relationships between variables, as well as feedback loops that influence system behavior over time. Arrows indicate the direction of influence between factors, while the polarity of relationships (positive or negative) reflects whether a change in one variable leads to an increase or decrease in another. The model is structured around three main outcome variables: cost, supply chain resilience, and procurement decision quality. These variables represent the primary objectives of procurement processes and act as aggregation points for the influence of multiple interconnected factors. External factors, such as geopolitical stability, market price volatility, and regulatory conditions, form the broader environmental context in which procurement decisions are made. Internal factors, including product characteristics, inventory capacity, and supply chain complexity, reflect operational constraints within the organization. Organizational and system-related factors – such as procurement maturity and AI-supported decision-making capability – determine the ability of the organization to effectively process information and respond to environmental changes. The diagram also highlights the central role of certain highly connected variables, particularly supplier base availability, which acts as a key node influencing multiple aspects of the procurement system. This high level of connectivity indicates its critical importance in shaping both cost-related outcomes and supply chain resilience. Overall, the CLD provides a holistic representation of procurement decision-making as a dynamic and interconnected system, where changes in one area may propagate through multiple pathways, affecting overall performance. The model supports the identification of leverage points, where analytical tools, including AI-based systems, can be applied to improve decision quality and organizational adaptability. This analysis allows for determining the relative importance of individual variables within the model structure and identifying factors that serve as key nodes within the system (tab. 2).

Table 2. Criteria strength and importance

Criterion name	No. of connections
Supplier Base Availability	7
Costs	5
Supply Chain Complexity	5
Technological Complexity (of Production\Service)	5
Supply Chain Resilience	5
Geopolitical Stability (Uncertainty)	4
Supply Lead Time	4

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Regulatory Environment	4
Market Price Volatility	4
Inventory Capacity	4
Supplier Switching Costs	4
Supplier Market Structure (competitive vs. monopolistic)	3
Product Customization Level	3
Buyer Attractiveness	3
Procurement Maturity	3
Procurement Decision Quality	2
AI-Supported Decision-Making Capability	2
Inventory Holding Costs	1

Source: own elaboration.

The results indicate that more than half of the criteria analyzed (10 out of 18) are characterized by a high level of connectivity, having between four and five relationships with other elements of the model. This means that a significant number of the variables included in the developed model play an important role within the system of relationships influencing the procurement decision-making process.

The criterion with the highest number of connections is Supplier Base Availability, which has seven relationships with other variables in the model. This result suggests that, within the conceptual framework developed by the author, the availability and size of the supplier base constitute one of the key, and potentially fundamental, criteria influencing procurement decision-making processes.

The importance of this factor stems from the fact that supplier availability reflects several other parameters describing the nature of the supply market and the characteristics of a given product or service. In particular, it may indicate the level of product or service standardization (e.g., widely available products compared to customized solutions), the technological complexity of the production process, the level of legal regulation within a given industry, or the structure of the supplier market. At the same time, the size and availability of the supplier base may influence the level of cost risk, market price volatility, and potential delivery lead times.

Within the developed model, three main directions to which the analyzed criteria converge were also identified. These are cost, supply chain resilience, and procurement decision quality. These factors represent key outcomes of decision-making processes in procurement management while simultaneously integrating the influence of multiple intermediate variables.

Among these directions, cost remains the most frequently analyzed and dominant decision criterion in business practice. In many enterprises, procurement decisions are still largely driven by the optimization of purchase costs or the total cost of ownership (TCO). However, it should be emphasized that achieving a specific cost level results from the combined influence of many intermediate factors, such as supplier availability, supplier market structure, supply chain complexity, and the level of legal regulation. Changes in these areas may indirectly, yet significantly, influence the final economic outcome of procurement decisions.

At the same time, the growing importance of risk and uncertainty in the economic environment means that supply chain resilience is increasingly crucial to procurement process analysis. The ability of organizations to maintain supply continuity under disruption conditions is becoming a key element of procurement management strategies, particularly in the context of global events such as geopolitical conflicts, energy crises, and logistical disruptions.

The model also includes a third key area, procurement decision quality. This factor is directly related to the level of procurement maturity within the organization and the possibility of utilizing advanced analytical tools, including AI-based decision support systems. As the complexity of the business environment increases, the importance of systems supporting data analysis and identifying relationships among multiple variables influencing procurement processes also grows.

In order to structure the analyzed variables, the author divided them into three main groups. The first group consists of external factors, including elements largely (or entirely) independent of the organization, such as geopolitical stability, legal regulations, market price volatility, and supplier market structure. The second group includes internal factors, resulting from the specific characteristics of the enterprise's operations, including product specification requirements, the level of product customization, and storage and inventory management capabilities. The third category consists of systemic or organizational factors, including the level of procurement maturity within the organization, the availability of analytical competencies, and the organization's ability to utilize decision-support tools based on data analytics and artificial intelligence.

This approach facilitates a more comprehensive understanding of the relationships between factors influencing procurement decision-making processes and indicates potential areas for the application of analytical tools and decision-support systems in procurement management.

5. CONCLUSION

This paper addresses the problem of decision-making in procurement processes under conditions of increasing uncertainty and complexity, as described by the VUCA and BANI frameworks.

The aim of the study is to develop a conceptual model that integrates multi-criteria decision-making (MCDM) methods with artificial intelligence and data mining supportive tools.

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Based on a literature review and practical experience, a conceptual model is proposed in the form of a causal loop diagram (CLD), illustrating the relationships between external, internal, and organizational factors influencing procurement decisions. The results indicate that supplier base availability plays a central role in the model, acting as a key node interconnected with multiple criteria.

Three main dimensions of procurement decision-making are defined: cost, supply chain resilience, and procurement decision quality.

The study highlights the growing importance of AI-based tools in data analysis and decision support, while also addressing current limitations related to data quality and organizational maturity.

This study addressed the research question of how artificial intelligence can be integrated with multi-criteria decision-making approaches to support procurement decisions under conditions of high uncertainty characteristic of VUCA/BANI environments. The study also provides answers to the research questions formulated in the introduction. Regarding R1, procurement decision-making is influenced by a combination of external environmental factors, internal operational constraints, and organizational capabilities. Regarding R2, AI complements traditional MCDM methods by improving data processing, pattern recognition, and predictive analysis while preserving the need for managerial judgement. Finally, concerning R3, effective AI-supported procurement requires organizational maturity, data quality, analytical competencies, and integration of AI tools into existing decision-making processes.

By combining insights from the literature with a conceptual modeling approach, the paper proposed a causal loop-based framework capturing the interactions between environmental factors, organizational capabilities, and analytical tools. The results indicate that procurement decision-making should be understood as a dynamic and interconnected system, in which multiple variables simultaneously influence key outcomes such as cost, supply chain resilience, and procurement decision quality. The model developed here demonstrates that both external factors (e.g., geopolitical instability, market volatility), internal operational conditions (e.g., product complexity, inventory capacity), and organizational capabilities (e.g., procurement maturity, analytical competencies) jointly shape decision processes. A key finding of the study is its identification of highly connected variables within the system, particularly supplier base availability, which plays a central role in influencing multiple dimensions of procurement performance. The structural analysis of the model further shows that improving procurement outcomes requires a systemic approach that accounts for interdependencies and feedback effects rather than isolated optimization of individual criteria. In this context, artificial intelligence emerges as a supporting mechanism rather than a standalone solution.

The findings suggest that AI-based tools can enhance procurement decision-making by improving data processing, identifying hidden relationships, and supporting multi-criteria analysis. However, their effectiveness depends on organizational readiness, data quality, and the ability to integrate analytical insights into

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managerial decision processes. This highlights the continued importance of human oversight and the need for hybrid decision-making models combining analytical and managerial expertise.

The main contribution of this paper lies in the development of an integrated conceptual framework that connects MCDM approaches, AI capabilities, and environmental uncertainty within a single model. This contributes to the existing literature by addressing the gap between fragmented research streams and providing a holistic perspective on procurement decision-making in complex environments. The study is subject to limitations, as the proposed model is conceptual and has not been empirically validated. The relationships between variables are derived from the literature and theoretical reasoning, which may not fully capture the complexity of real-world organizational contexts. Future steps should therefore validate the proposed framework through multiple complementary approaches, including case studies, Delphi-based expert evaluation, simulation modelling, and questionnaire surveys involving procurement professionals operating in different industries.

The proposed model provides a foundation for further empirical research and may support organizations in the gradual implementation of data-driven approaches in procurement management. AI-supported decision-making in procurement is rapidly evolving, offering transformative benefits in efficiency, cost savings, and transparency. However, challenges such as data integration, ethical concerns, and organizational readiness must be addressed to fully realize its potential. Future research should focus on human-centric AI, regulatory alignment, and continuous system improvement to ensure sustainable and effective adoption. Unlike previous studies focusing separately on AI, MCDM, or supply chain resilience, the proposed framework integrates these perspectives into a single systemic representation based on causal loop modelling, thereby extending the theoretical understanding of procurement decision-making under uncertainty.

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PODEJMOWANIE DECYZJI W ZAKUPACH WSPOMAGANE SZTUCZNĄ INTELIGENCJĄ: MODEL KONCEPCYJNY DLA INTELIGENTNYCH I ODPORNYCH ŚRODOWISK BIZNESOWYCH

Streszczenie

Niniejszy artykuł dotyczy integracji sztucznej inteligencji (AI) z wielokryterialnym procesem decyzyjnym (MCDM) w procesach zakupowych w warunkach wysokiej niepewności, charakterystycznej dla środowisk VUCA/BANI. Na podstawie ustrukturyzowanego przeglądu literatury opracowano koncepcyjny diagram pętli przyczynowo-skutkowej (CLD) w celu modelowania relacji między czynnikami zewnętrznymi, wewnętrznymi warunkami organizacyjnymi a możliwościami decyzyjnymi wspieranymi przez AI. Wyniki wskazują, że decyzje zakupowe należy rozumieć jako dynamiczny system, na który wpływają współzależności między zmiennymi, takimi jak dostępność bazy dostawców, zmienność rynku i dojrzałość zakupowa. Model identyfikuje kluczowe czynniki wpływające na koszty, odporność łańcucha dostaw i jakość decyzji, podkreślając centralną rolę silnie powiązanych

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zmiennych. Badanie przyczynia się do opracowania zintegrowanych ram wspierających wdrażanie AI w procesach decyzyjnych w procesach zakupowych. Proponowany model stanowi podstawę dalszych badań empirycznych i może wspierać organizacje w stopniowym wdrażaniu podejść opartych na danych w zarządzaniu zakupami. Przyszłe badania powinny koncentrować się na sztucznej inteligencji zorientowanej na człowieka, dostosowaniu przepisów i ciągłym doskonaleniu systemów, aby zapewnić zrównoważone i efektywne wdrożenie.

Słowa kluczowe: AI, VUCA, BANI, diagram pętli przyczynowej

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