

MULTI-CRITERIA DECISION SUPPORT SYSTEMS USING GENERATIVE AI: AN APPLIED EXCEL-BASED SUPPLIER RANKING CASE STUDY

Faruk Unkić^{1*}, Haris Hojkurić²

¹Associate Professor, University of Zenica, Kalošević 23, 74260 Tešanj, Bosnia and Herzegovina

²Senior Assistant, Assistant to the Municipal Mayor, Municipality of Novo Sarajevo, Zmaja od Bosne 55, 71000 Sarajevo, Bosnia and Herzegovina.

*Corresponding Author

Faruk Unkić

E-mail: faruk.unkic@unze.ba

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Abstract: In modern organizations, decision-making rarely relies on a single indicator, as business problems are typically shaped by conflicting requirements such as lower cost, higher quality, lower risk, faster delivery, and greater reliability. In this context, decision support systems (DSS) and business intelligence (BI) provide a benefit framework for structuring problems, processing data, and evaluating alternatives. At the same time, generative AI, especially large language models, is becoming increasingly available as an auxiliary tool for formulating formulas, explaining results, preparing reports, and interpreting findings. However, its use in business decision-making requires transparency, source verification, and clear human accountability.

This paper aims to demonstrate, both theoretically and practically, how multi-criteria decision-making can be implemented as a lightweight DSS model in Microsoft Excel and how generative AI can be incorporated as a supportive, rather than autonomous, component of decision-making. The Simple Additive Weighting / Weighted Sum Model (SAW/WSM) is applied through the normalization of cost and benefit criteria, weighting, and sensitivity analysis based on changes in the weight assigned to price. The case study includes three suppliers and four criteria: price, quality, technical support, and delivery time.

The results show that under the initial criterion weights (0.4, 0.3, 0.2, 0.1), TechSol achieves the highest overall score (0.9027). However, after increasing the weight of price to 0.6 and proportionally rescaling the other weights, GlobalIT becomes the top-ranked supplier (0.9022). This finding confirms that DSS should not be seen as tools that provide a single definitive answer, but rather as transparent frameworks for examining the consequences of different managerial priorities. The paper concludes that an Excel-based MCDM model is a practical, accessible, and reproducible solution for operational decision-making in small and medium-sized organizations, but that its reliability depends on data quality, spreadsheet error control, and the responsible use of generative AI.

Keywords: business intelligence, decision support systems, multi-criteria decision-making, SAW/WSM, Microsoft Excel, generative artificial intelligence, supplier ranking, sensitivity analysis.

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1. Introduction

The modern business environment is marked by rapid growth in the volume of data, accelerated changes in market conditions and an increasingly pronounced need to make decisions quickly, with sound justification and with the lowest possible level of risk. In such circumstances, organizations can no longer function effectively if key decisions remain based solely on experience, intuition, or partial information. An integrated framework is needed that allows for the collection of relevant data, the analytical processing of data, comparison of alternatives and transparent explanation of choices. It is in this space that business intelligence, decision support systems and multi-criteria decision-making meet.

Decision support systems are described in the classical literature as computer-aided systems that help decision-makers solve complex and semi-structured problems by combining data, models, and user interaction. Their development has accompanied the transition from early model-oriented systems to data-rich, collaborative, and intelligent decision-making environments. At the same time, business intelligence has been developed as an infrastructure for data collection, integration, storage and analysis, thus becoming the database for many DSS applications. In modern organizations, BI and DSS are no longer seen as strictly separate systems, but as complementary layers of a broader analytical ecosystem.

DSS approaches have a special relevance in multi-criteria problems, such as supplier selection. In such situations, the decision does not depend on a single criterion, for example price, but on the simultaneous consideration of several interrelated or competing indicators, such as quality, delivery time, support, risk or reliability. In the literature, supplier selection is recognized as one of the classic problems of multi-criteria decision-making, precisely because it requires an explicit definition of priorities and a transparent evaluation of alternatives.

In the last two years, generative artificial intelligence has given an additional impetus to this field. Large language models can help users formulate problems, explain formulas, summarize results, and prepare reports, but they are also prone to errors, superficial generalizations, and hallucinations. Therefore, in the academic and business context, the question of how to incorporate generative artificial intelligence (AI) responsibly is increasingly important: as an auxiliary layer that speeds up work and reduces cognitive load, but does not take human responsibility for the correctness of the results.

Starting from these assumptions, the aim of this paper is to show how a multi-criteria DSS model can be implemented in a widely

available tool such as Microsoft Excel, and to show how generative artificial intelligence can support, but not replace, the decision-making process. The paper is focused on a case study of supplier ranking, using a simple additive model SAW/WSM, normalization of criteria and sensitivity analysis through weight change. The research question is: how does the transparent integration of BI logic, DSS model, multi-criteria analysis and generative artificial intelligence contribute to better, more understandable and more reproducible business decision-making?

The paper makes three contributions. First, it offers a methodologically ordered and easily reproducible example of multi-criteria decision-making in Excel. Second, it shows that sensitivity analysis is not an add-on but an essential part of a serious DSS approach, because a change in priorities can also change the final choice. Thirdly, it introduces a practical framework for the responsible use of generative AI in business analytical work, with an emphasis on verification, auditability and human responsibility.

2. Theoretical Framework

2.1. Business intelligence as a data foundation for decision-making

Business Intelligence is a set of concepts, processes, technologies, and tools aimed at converting data into decision-making information and knowledge. Its basic function is not only reporting, but systematic support for understanding business performance, trends and deviations. BI systems typically integrate data from multiple sources, go through extraction, transformation, and loading processes, then organize it into data warehouses or data marts, and enable its analysis through OLAP, visualization, dashboards, and other analytical techniques.

The role of a BI system is particularly important because organizations often have large amounts of heterogeneous, dispersed and inconsistent data. Without a process of standardization and integration, it is difficult to talk about serious data-driven decision-making. Chen, Chiang, and Storey point out that modern business intelligence and analytics paradigms are evolving from classical analytics based on structured data to a broader analytics ecosystem in which data processing, visualization, and modeling form the basis for creating business impact. Yeoh and Koronios further emphasize that the success of a BI system depends not only on the technology, but also on the quality of the data, management support, alignment with business goals and user competencies.

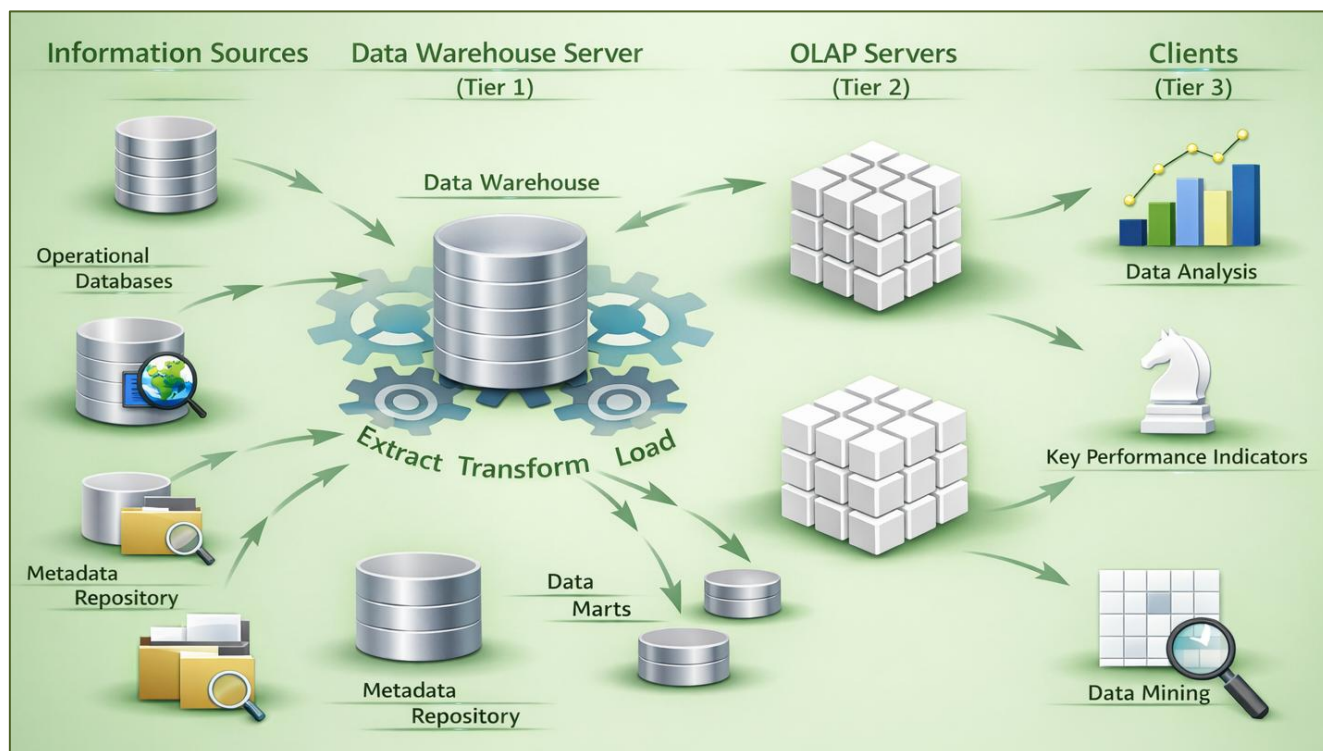


Figure 1. Conceptual architecture of business intelligence: data sources, ETL processes, data warehouse, analytical layer, and reporting.

In the context of this paper, BI is not seen as an end in itself, but as a data layer on which the DSS model can be built. In other words, BI answers the question of where data comes from and how it is organized, while DSS answers the question of how alternatives are compared based on this data and formulates recommendations.

2.2. Decision support systems

For decades, DSS literature has emphasized that decisions in organizations are not always fully structured. DSS is a technology framework that helps managers and analysts solve semi-structured and unstructured problems using data, models, and interactive tools. Arnott and Pervan point out that the DSS discipline has historically developed several subareas: personal DSS systems, group DSS systems, data warehouses, enterprise reporting, knowledge management, and other forms of decision-making supported by information technology. What connects these approaches is the focus on the quality of the decision, not just on data processing.

DSS systems can be model-oriented, data-oriented, communication-oriented, or knowledge-based. Model-oriented systems emphasize mathematical and optimization models. Data-driven systems are more reliant on big data sets and analytics. Knowledge-based DSS rely on expert rules, heuristics, and inference logic. In practice, modern DSS often combine several of these approaches, especially when connecting to BI infrastructures and AI tools.

The decision-making process in the DSS context usually includes the identification of problems, the definition of criteria and alternatives, the collection and processing of data, the construction of models, the evaluation of possible solutions, the selection, and subsequent monitoring of the consequences of the decision. Hence an important feature of the DSS: it does not only give a "result", but also preserves a trace of assumptions, parameters and relationships between criteria. That is why DSS has a high practical value in business situations where it is necessary to justify why a certain alternative was chosen.

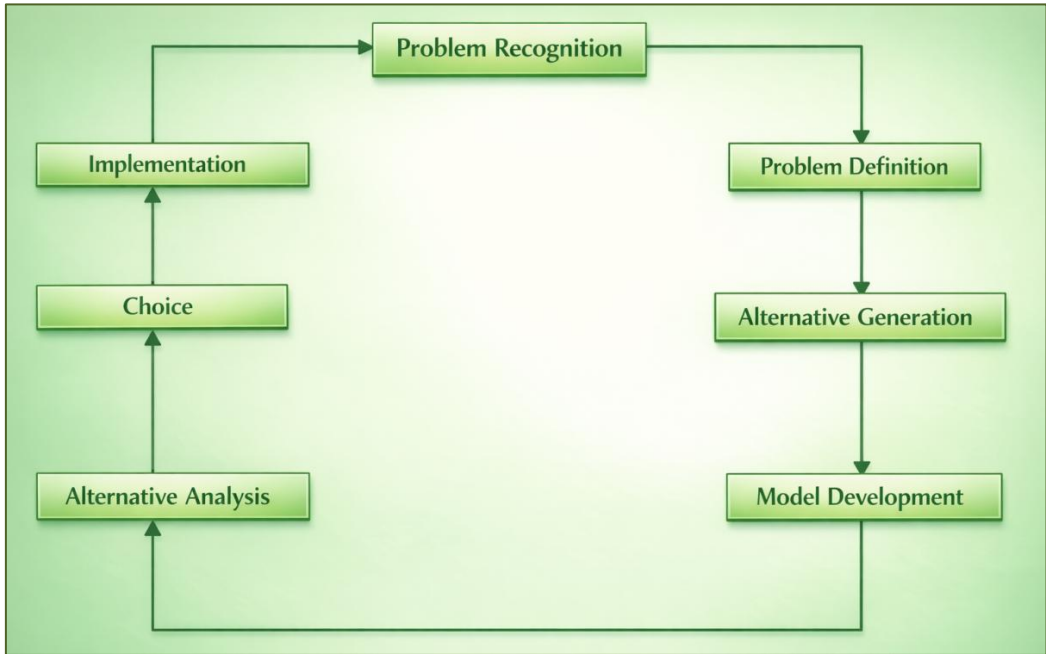


Figure 2. Phases of the decision-making process in the DSS environment: problem definition, generation of alternatives, modeling, evaluation and selection.

2.3. Connection between BI and DSS systems

In practice, BI and DSS should not be seen as competing, but as complementary concepts. BI is primarily focused on collecting, integrating, analyzing, and presenting data, while DSS takes data

and uses it to evaluate alternatives and support choice. This means that BI provides the information context, and DSS provides the decision-making framework. In successful organizations, BI and DSS together form part of a broader data-driven management system.

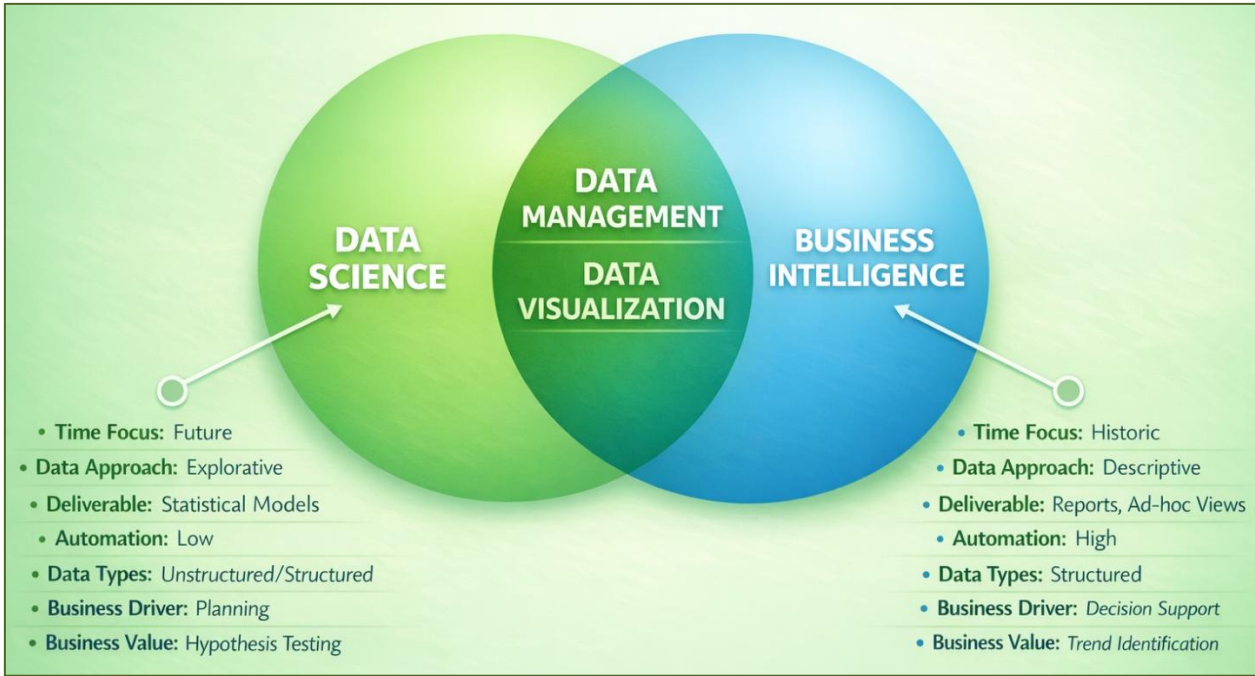


Figure 3. The relationship between business intelligence, analytics and decision support systems.

2.4. Multi-criteria decision-making and the problem of supplier selection

Multi-criteria decision-making starts from the assumption that many real problems cannot be solved by optimizing according to one indicator. In the field of procurement and supply chain management, supplier selection is a typical example of such a problem. In their review paper, Ho, Xu and Dey show that suppliers in modern practice are evaluated through several criteria, not just price, and that MCDM approaches have become a standard framework for supplier evaluation and selection. Criteria may include cost, quality, flexibility, delivery time, technical support, environmental and social indicators, logistical reliability and other dimensions.

There are a number of MCDM methods in the literature: AHP, TOPSIS, VIKOR, ELECTRE, PROMETHEE, SAW/WSM and others. Some of them are suitable for more complex hierarchical

assessments and partial comparisons, while others are better suited for fast and transparent operational use. In the late 1990s, Zanakis et al. pointed out that simple additive approaches, such as SAW, behave competitively in many scenarios compared to more complex methods, especially when the goal is model comprehensibility and practical applicability.

For the purposes of this paper, the SAW/WSM method was chosen for three reasons. First, it is transparent and easy to understand for users who are not specialists in operational research. Secondly, it is easily implemented in Excel without additional specialized software. Third, it is suitable for demonstrating the basic principles of DSS: normalization, weighting, aggregation, and sensitivity analysis. Such a choice does not mean that SAW is universally the best method, but that it is adequate for the goal of the paper – the presentation of an operational, auditable and easily applicable model.

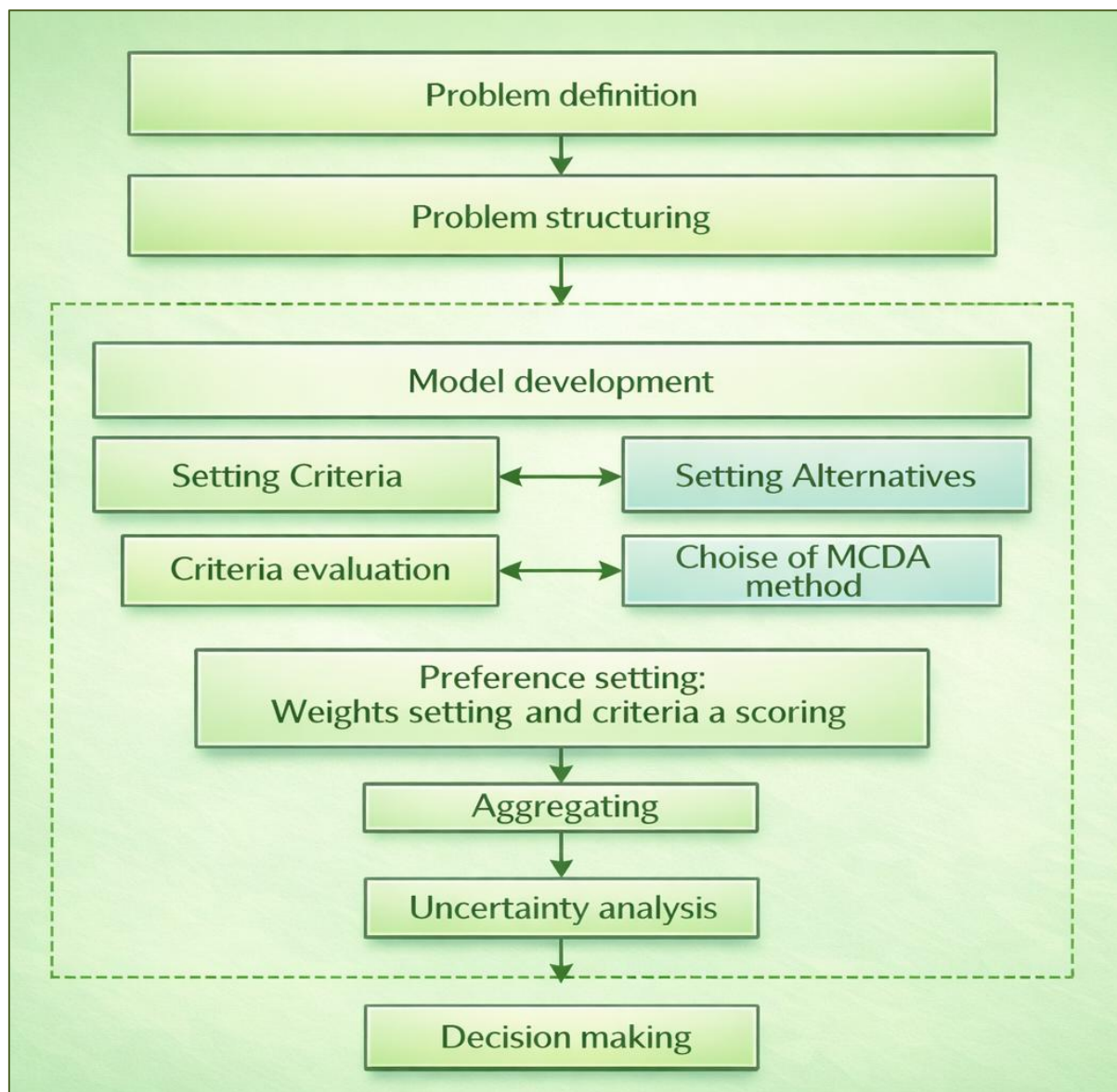


Figure 4. Steps of multi-criteria decision-making: definition of problems, criteria and alternatives, assignment of weights, aggregation and sensitivity analysis.

2.5. Generative Artificial Intelligence in the BI/DSS Environment

Environment

Modern BI and DSS systems are increasingly being upgraded with AI components. Alghamdi and Al-Baity show that AI-driven augmented analytics can speed up data preparation, modeling, visualization, and insights generation, but that it cannot completely replace human decision-making. Within this framework, generative AI becomes a new type of support: instead of directly modeling a decision, it helps the user work with data, formulas, interpretations, and textual explanations.

Microsoft's documentation confirms that Copilot in Excel can help users create and understand formulas, analyze data, generate insights, and perform auxiliary actions within worksheets. This means that generative AI can have real operational value in a spreadsheet environment, especially for users who have domain knowledge but are not experts in complex Excel functions or formal models. At the same time, Microsoft specifically documents

both Scenario Manager and Solver as standard tools for what-if analysis and optimization, making them a natural backbone for lightweight DSS implementations.

Nevertheless, generative AI should not be used uncritically as a source of facts or definitive recommendations. The GPT-4 technical report and review papers on hallucinations of large language models show that such systems can produce convincing but inaccurate or incompletely substantiated content. UNESCO and NIST emphasize that human control, transparency, understanding of limitations, and risk management must be ensured when using generative AI. ICMJE's recommendations further emphasize that humans, not AI tools, are responsible for the accuracy, integrity, and originality of content, and that AI cannot be the author of the paper. In the context of this paper, this means that generative AI is treated as an auxiliary layer for speeding up work and explaining the model, but not as an independent decision-maker.

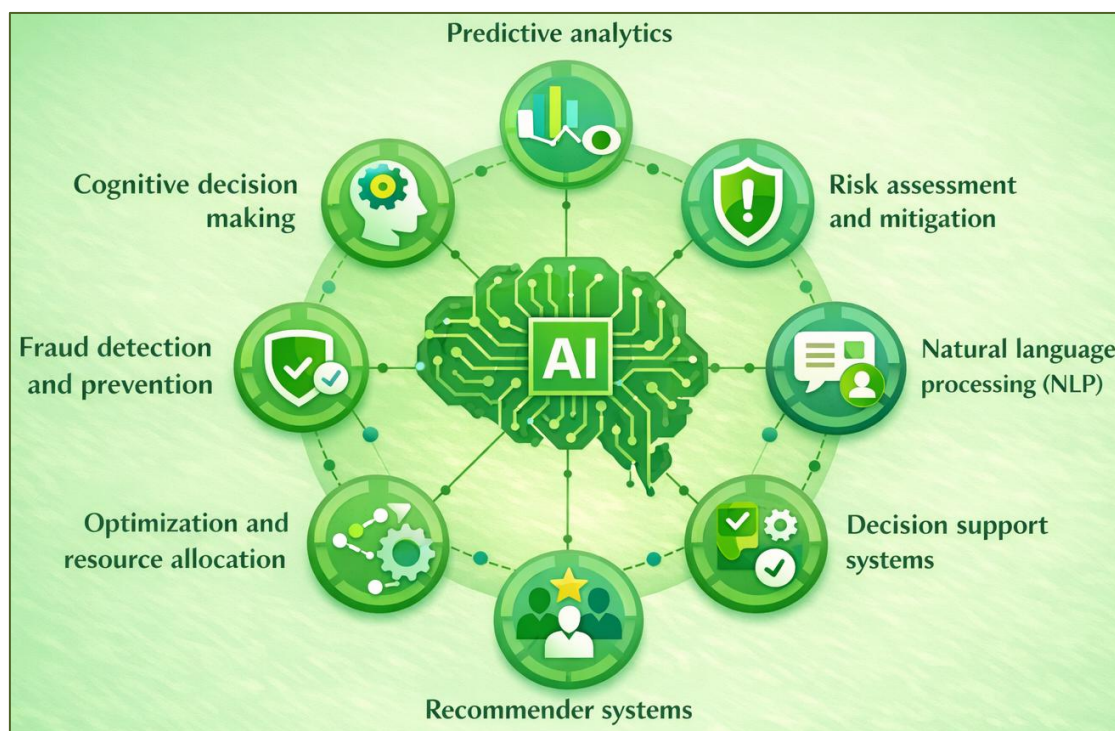


Figure 5. Examples of AI techniques relevant to BI and DSS systems.

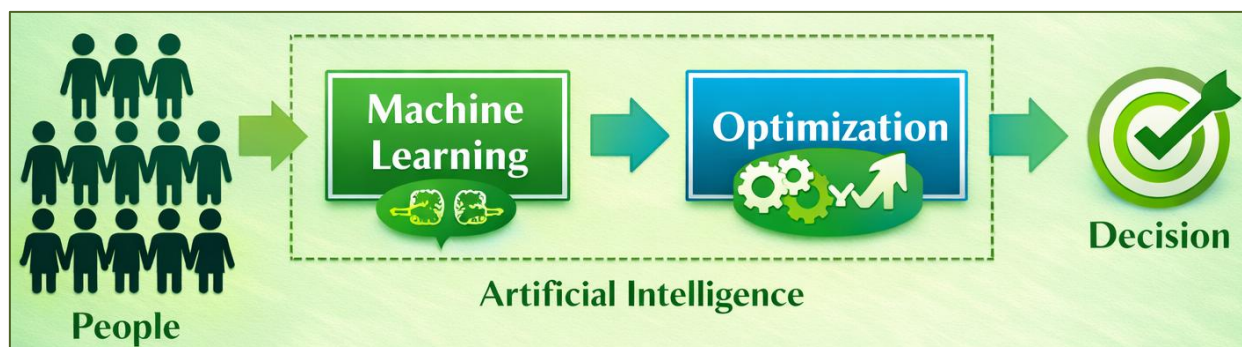


Figure 6. Integration of human, model and AI support in the modern DSS environment.

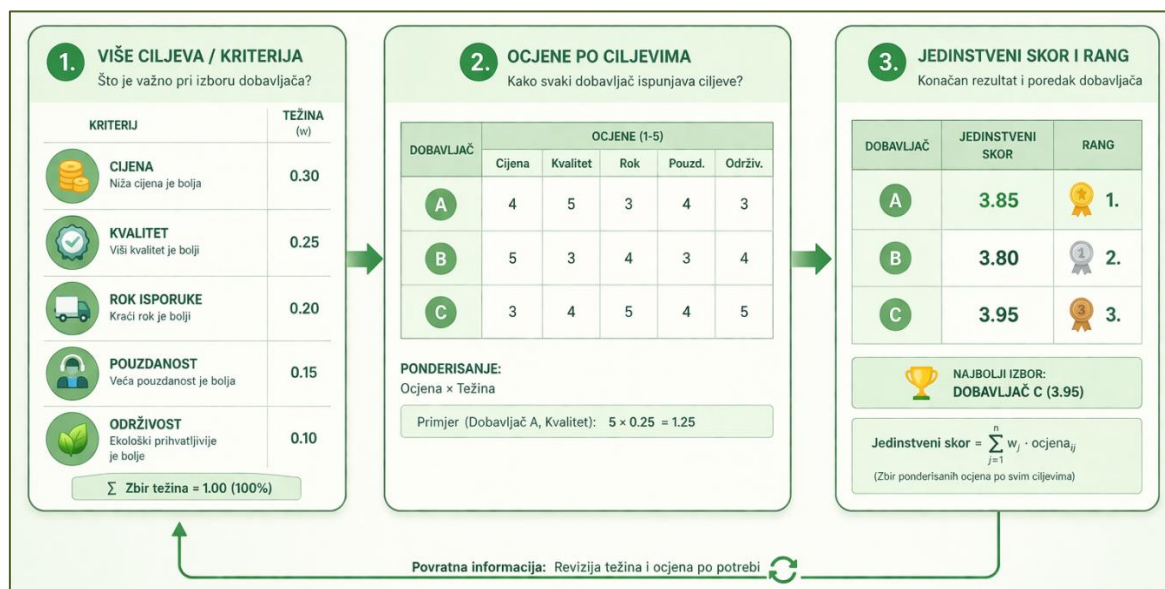


Figure 7. The logic of multi-objective ranking: from multiple goals to a single score.

2.6. Empirical findings on the effects of generative AI on knowledge work

To position generative AI within the DSS, it is not enough to rely only on the technical descriptions of the models; it is also important to take into account the empirical findings on how these systems affect the actual work. Brynjolfsson, Li and Raymond in their paper on generative AI in the workplace show that access to AI suggestions can increase the productivity of individual workers and improve the work experience, but at the same time emphasize that the effects are not uniform and that they depend on the task profile and user experience. Of particular importance, the authors note a greater benefit for less experienced workers, suggesting that AI may play the role of a "leveler" of certain competency differences, but not necessarily a substitute for deep domain knowledge.

Dell'Acqua and collaborators are sending a similar message through the concept of "jagged technological frontier". Their finding that AI assistance can improve performance in some tasks and worsen it in others, even when the tasks seem similar at first glance, is particularly relevant to the DSS context. Business decision-making is rarely homogeneous: it includes routine, structured, semi-structured and interpretive activities. Generative AI can be very successful in linguistic summarization, formula suggestion, or report organization, but worse when it comes to assessing tacit organizational logic, hidden risks, institutional specifics, or value conflicts between criteria.

Eloundou and colleagues further show that large language models have the potential to affect a large number of jobs and tasks, but this does not mean that every affected task becomes automated. For the DSS, this means that the way of working is transformed: some activities are accelerated, some are reorganized, and some get a greater need for human supervision. In the context of this paper, this is especially important because the Excel model is not just a numerical mechanism; It is also an organizational artifact that needs to be understood, explained, and defended against other actors. Generative AI can help shape that explanation, but its credibility remains conditioned by the quality of human verification.

2.7. AI risk management in the decision-making process

DSS systems are by their nature aimed at reducing uncertainty, but the introduction of generative AI also introduces a new category of risk. NIST AI RMF emphasizes that AI risk management is inseparable from the issues of trustworthiness, transparency, security, fairness, and accountability. Such an approach is also highly applicable in business decision-making, as DSS decisions are often associated with financial, operational and reputational consequences.

In the context of this paper, at least four groups of AI risks can be distinguished. The first is informational risks – the generation of inaccurate, outdated or fabricated claims. The second is model risks – a misunderstanding of the logic of a formula, a criterion or an interpretation of sensitivity. The third group consists of process risks – excessive user reliance on AI output without additional verification. The fourth is made up of ethical and governance risks – the lack of clarity of responsibilities, the absence of records of where AI was used, and the inability to audit it later.

For these reasons, the responsible integration of generative AI into DSS work should be based on several principles: transparency, verifiability, human oversight, proportionality, and documentation of use. Transparency means that the user knows where the AI has helped. Verifiability means that each key output can be tested through source data or independent calculation. Human control means that the decision-maker remains responsible for the final judgment. Proportionality means that AI is used where it really brings benefits, not just because it is available. Documenting usage means that an organization can subsequently reconstruct the workflow and determine who, when, and at what stage used AI support.

2.8. Why the emphasis in this paper is on generative and not just general artificial intelligence

The term general or broad artificial intelligence often refers to a large set of techniques: machine learning, neural networks, expert systems, fuzzy logic, optimization, and more. This paper, however, puts a special focus on generative artificial intelligence because it

is currently becoming the most accessible form of AI support for users working in everyday business tools.

This is important for two reasons. First, generative AI differs from classic predictive models in that it communicates directly with the user in natural language and can assist in textual, explanatory, and formulation tasks. Secondly, it is this accessibility that increases the likelihood of its widespread and often uncontrolled use. Therefore, it is academically relevant to consider not only its benefits, but also the conditions under which its integration remains responsible and methodologically acceptable.

That is why this paper does not claim that generative AI "improves the decision" on its own. It is more accurate to say that it can improve the process of working around a decision – speed up preparation, facilitate explanation and support understanding – but only when the basic data is of high quality, the model is clearly defined, and the user is able to distinguish a suggestion from a verified fact.

3. Research Methodology

3.1. Research design

The paper is conceived as a theoretical and practical case study. The theoretical part systematizes relevant concepts from BI, DSS, MCDM and generative artificial intelligence, while the practical part demonstrates the implementation of a simple multi-criteria model in Microsoft Excel. The chosen research design is not focused on statistical generalization, but on the analytical demonstration of a procedure that can be reproduced and adapted to related business situations.

The case study refers to the selection of a strategic supplier of IT equipment/services for the modernization of the company's server infrastructure. The problem lends itself to multi-criteria analysis because it involves the simultaneous consideration of financial, qualitative and operational indicators. In such circumstances, one indicator cannot be enough to make a rational decision.

3.2. Alternatives and criteria

The analysis includes three alternatives (suppliers):

- TechSol,
- GlobalIT,
- EcoData.

The decision-makers have defined four key criteria on the basis of which the multi-criteria ranking will be carried out:

1. Price (BAM, Bosnia and Herzegovina convertible marks) – cost criterion, it needs to be minimized.
2. Quality of equipment (grade 1–10) – a benefit criterion, it needs to be maximized.
3. Technical support (grade 1–5) – a benefit criterion, it needs to be maximized.
4. Delivery time (number of days) – cost criterion, it needs to be minimized.

The choice of these criteria is theoretically justified because it includes financial rationality, quality of procurement and operational feasibility. Practically, these are the criteria that

management and procurement services actually use when evaluating suppliers.

3.3. Initial weights of the criteria

The initial weights of the criteria are:

- price 0.4
- quality 0.3
- support 0.2
- delivery time 0.1

The weights reflect the initial preference of the decision-maker that cost is paramount, but not dominant to the extent that it nullifies quality and support. It is important to emphasize that weights are not an "objective fact"; they are a normative expression of priorities and therefore must be explicitly presented and not implied.

3.4. Choice of the SAW/WSM method

The Simple Additive Weighting or Weighted Sum Model was chosen as the analytical model. The method is based on three steps: normalizing the criteria, weighting the normalized values, and summing the weighted results into a single alternative score. Its advantage is reflected in its simplicity, transparency and the possibility of easy implementation in the spreadsheet environment.

Let the decision matrix be denoted by $X = [x_{ij}]$, where i represents the alternative and j represents the criterion. After normalization, the matrix $R = [r_{ij}]$ is obtained.

The total score of the alternative is calculated by the formula:

$$S_i = \sum (w_j \cdot r_{ij}), \text{ for } j = 1, \dots, m$$

where is:

- S_i – total score of the alternative i ,
- w_j – weight of the criterion j ,
- r_{ij} – normalized value of the alternative i by criterion j .

The highest score indicates the most favorable alternative.

3.5. Normalization of criteria

Since the criteria have different units of measurement and different desirable orientations, they need to be normalized to a common scale. Standard normalization ratios are applied:

For benefit criteria:

$$r_{ij} = x_{ij} / \max_i(x_{ij})$$

For cost criteria:

$$r_{ij} = \min_i(x_{ij}) / x_{ij}$$

This choice is in line with practical MCDM implementations that require a fast, understandable and easily verifiable model. This ensures that the best value for each criterion gets a maximum normalized value of 1, while the other alternatives get relative values between 0 and 1.

3.6. Implementation in Microsoft Excel

Excel was chosen as the deployment environment because it is widespread, familiar to a large number of users, and flexible

enough to allow the construction of transparent DSS models without special programming. Its advantages in this work are:

- availability in most organizations,
- simplicity of creating formulas and tables,
- possibility of what-if analysis,
- ability to document assumptions and results,
- easy revision by other users.

In practical implementation, basic Excel formulas are used to determine the minimum and maximum, calculate normalized values and total score. For cost criteria, a formula of type =MIN(range)/value is used, and for benefit criteria, a formula of type =value/MAX(range) is used. The total score is calculated as the sum of the products with normalized values and the associated weights.

The following formulas illustrate the calculation logic:

- normalized price: =MIN(\$B\$5:\$B\$7)/B5
- normalized quality: =C5/MAX(\$C\$5:\$C\$7)
- normalized support: =D5/MAX(\$D\$5:\$D\$7)
- normalized delivery time: =MIN(\$E\$5:\$E\$7)/E5
- total score:
=(F5*\$B\$2)+(G5*\$C\$2)+(H5*\$D\$2)+(I5*\$E\$2)

3.7. The role of generative AI and trustworthiness controls

In this paper, generative artificial intelligence was not used as a source of ready-made decisions, but as an auxiliary tool in three groups of tasks:

1. for faster formulation and explanation of Excel formulas,

2. for linguistic summarization and interpretation of the results obtained,

3. for assistance in structuring reports and identifying possible scenarios.

To avoid the risks of hallucinations and uncritical reliance on AI outputs, the following controls have been put in place:

- each numerical value and each result is verified by direct calculation in Excel;
- theoretical claims are based on verifiable scientific and official sources;
- AI is not used as an author or as a source of bibliographic units without additional verification;
- the final interpretation of the results remains the responsibility of the researcher.

3.8. Sensitivity analysis

The sensitivity analysis was carried out through a scenario in which the weight of the price criterion increases from 0.4 to 0.6. The other weights are rescaled proportionally so that their sum remains 1:

- quality 0.2
- support 0.1333
- delivery time 0.0667

This scenario simulates a business situation in which an organization enters a more restrictive budget regime and gives more importance to cost than in the initial model. In DSS terms, sensitivity analysis makes it possible to examine the stability of the final ranking and recognize whether the choice is robust or depends on a change in preferences.

Table 1. Criteria, type of criteria and starting weights

Criterion	Type of criteria	Orientation	Starting weight
Price (BAM)	Cost	Minimization	0,4
Quality (1-10)	Benefit	Maximization	0,3
Technical support (1-5)	Benefit	Maximization	0,2
Delivery time	Cost	Minimization	0,1

Table 2. Controls on the Responsible Use of Generative Artificial Intelligence in Work

Area	Application of AI	Risk	Control measure
Excel formulas	Help with the formulation and explanation of formulas	Wrong formula	Manual testing in a worksheet
Interpretation of the results	Summarizing and explaining the findings	Superficial or inaccurate interpretation.	Check with numerical results
Literature	Help identify relevant topics	Fictional or inaccurate sources	Use only verifiable sources
Reporting	Linguistic editing and structuring	Over-reliance on AI text	Human editing and final responsibility

Table 3. Advantages and Limitations of the Excel-Based DSS Approach

Aspect	Advantages	Limitations
Availability	Widespread tool, low entry threshold	It is not a dedicated DSS platform.
Transparency	Visible formulas and parameters	Higher risk of user errors.
Flexibility	Quick adaptation to different problems	The model easily becomes confusing without discipline
Scenario analysis	What-If Analysis and Scenario Manager	Requires a well-structured worksheet

4. Research Results

4.1. Input data

Based on the business scenario, the following input values are defined:

- TechSol: price 50,000 BAM; quality 9; support 5; delivery time: 15 days
- GlobalIT: price 42,000 BAM; quality 7; support 3; delivery time (days) 10 days

- EcoData: price 47,000 BAM; quality 8; support 4; Delivery time (days) 20 days

TechSol offers the highest quality and the best technical support, but at the highest price. GlobalIT is the cheapest and has the shortest delivery time, but it is inferior in terms of quality and support. EcoData is an intermediate option that does not achieve the maximum by any criteria, but maintains a balanced profile.

G10 : X ✓ fx = (B10*\$B\$2)+(C10*\$C\$2)+(D10*\$D\$2)+(E10*\$E\$2)						
	A	B	C	D	E	F
1	Supplier	Price (BAM)	Quality (1-10)	Support (1-5)	Lead Time (days)	
2	Weights	0,4	0,3	0,2	0,1	
3						
4	RAW DATA					
5	TechSol	50.000	9	5	15	
6	GlobalIT	42.000	7	3	10	
7	EcoData	47.000	8	4	20	
8						
9	NORMALIZATION	Price	Quality	Support	Lead Time	TOTAL
10	TechSol	0,84	1	1	0,666666667	0,902666667
11	GlobalIT	1	0,777777778	0,6	1	0,853333333
12	EcoData	0,893617021	0,888888889	0,8	0,5	0,834113475
13						

Figure 8. Inputs, normalized values, and weighted total scores in an Excel model.

4.2. Normalization of criteria

By applying the previously defined formulas, the following normalized values were obtained:

For the price criterion (cost criterion, min = 42,000):

- TechSol: $42,000 / 50,000 = 0.8400$
- GlobalIT: $42,000 / 42,000 = 1,0000$
- EcoData: $42,000 / 47,000 = 0,8936$

For the quality criterion (benefit criterion, max = 9):

- TechSol: $9 / 9 = 1.0000$
- GlobalIT: $7 / 9 = 0.7778$
- EcoData: $8 / 9 = 0.8889$

For the support criterion (benefit criterion, max = 5):

- TechSol: $5 / 5 = 1.0000$
- GlobalIT: $3 / 5 = 0.6000$
- EcoData: $4 / 5 = 0.8000$

For the delivery time criterion (cost criterion, min = 10):

- TechSol: $10 / 15 = 0.6667$
- GlobalIT: $10 / 10 = 1.0000$
- EcoData: $10 / 20 = 0.5000$

The results show the expected logic of normalization. GlobalIT achieves maximum values on the price and delivery-time criteria, while TechSol dominates on quality and support. EcoData has balanced, but lower values than the leading alternatives on each individual criterion.

4.3. Weighted aggregation in the baseline scenario

Using the initial weights (0.4, 0.3, 0.2, 0.1), the following total scores were obtained:

$$\begin{aligned}
 &\text{TechSol: } (0.4 \times 0.8400) + (0.3 \times 1.0000) + (0.2 \times 1.0000) + (0.1 \times 0.6667) \\
 &= 0.3360 + 0.3000 + 0.2000 + 0.0667 \\
 &= 0.9027
 \end{aligned}$$

$$\begin{aligned} \text{GlobalIT: } & (0.4 \times 1.0000) + (0.3 \times 0.7778) + (0.2 \times 0.6000) + (0.1 \times 1.0000) \\ & = 0.4000 + 0.2333 + 0.1200 + 0.1000 \\ & = 0.8533 \end{aligned}$$

$$\begin{aligned} \text{EcoData: } & (0.4 \times 0.8936) + (0.3 \times 0.8889) + (0.2 \times 0.8000) + (0.1 \times 0.5000) \\ & = 0.3574 + 0.2667 + 0.1600 + 0.0500 \\ & = 0.8341 \end{aligned}$$

Based on this, the ranking list in the basic scenario reads:

1. TechSol – 0.9027
2. GlobalIT – 0.85333
3. EcoData – 0.8341

The result shows that the initial model favors TechSol. Although it is not the cheapest or fastest, it makes up for this shortcoming with the best quality and support, and it is these criteria that together carry half of the total weight of the model. In other words, the managerial priorities from the initial scenario reward a quality and safer option more than pure cost efficiency.

4.4. Presentation of the Formula Implementation

One of the important features of this model is that every step is easily verifiable. Unlike the "black box" that the user does not have access to, the Excel model clearly shows how each individual score was obtained. This is extremely important in the context of organizational decision-making, as transparency facilitates the revision, reasoning and eventual modification of assumptions.

G10 $= (B10 * \$B\$2) + (C10 * \$C\$2) + (D10 * \$D\$2) + (E10 * \$E\$2)$						
	A	B	C	D	E	F
1	Supplier	Price (BAM)	Quality (1-10)	Support (1-5)	Lead Time (days)	
2	Weights	0,4	0,3	0,2	0,1	
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8						
9	NORMALIZATION	Price	Quality	Support	Lead Time	TOTAL
10	TechSol	0,84	1	1	0,666666667	0,902666667
11	GlobalIT	1	0,777777778	0,6	1	0,853333333
12	EcoData	0,893617021	0,888888889	0,8	0,5	0,834113475
13						

Figure 9. Example Excel formulas for normalizing criteria and calculating the total score of the alternative.

4.5. Sensitivity analysis: increasing the weight of the price criterion

When the weight of the price criterion is increased from 0.4 to 0.6, and the other weights are proportionally scaled to quality 0.2, support 0.1333 and delivery time 0.0667, the following scores are obtained:

$$\begin{aligned} \text{TechSol: } & (0.6 \times 0.8400) + (0.2 \times 1.0000) + (0.1333 \times 1.0000) + (0.0667 \times 0.6667) \\ & = 0.5040 + 0.2000 + 0.1333 + 0.0444 \\ & = 0.8818 \end{aligned}$$

$$\begin{aligned} \text{GlobalIT: } & (0.6 \times 1.0000) + (0.2 \times 0.7778) + (0.1333 \times 0.6000) + (0.0667 \times 1.0000) \\ & = 0.6000 + 0.1556 + 0.0800 + 0.0667 \\ & = 0.9022 \end{aligned}$$

$$\begin{aligned} \text{EcoData: } & (0.6 \times 0.8936) + (0.2 \times 0.8889) + (0.1333 \times 0.8000) + (0.0667 \times 0.5000) \\ & = 0.5362 + 0.1778 + 0.1067 + 0.0333 \\ & = 0.8539 \end{aligned}$$

The new ranking list reads:

1. GlobalIT – 0.90222
2. TechSol – 0.88183
3. EcoData – 0.8539

This result is particularly important because it shows that increasing the significance of price changes the final choice. A detailed calculation confirms: when cost becomes an extremely dominant criterion, GlobalIT takes the lead. This means that the model is not completely robust to changing preferences, but it is precisely this sensitivity that represents valuable information for the decision-maker.

4.6. Summary of results

The results of the case study confirm four important findings:

1. a multi-criteria model in Excel can produce a clear and verifiable ranking of alternatives;
2. the choice of the "best" supplier depends on the explicitly set weights of the criteria;
3. sensitivity analysis reveals that the initial decision is not absolute, but conditional;
4. a transparent model allows the user to recognize under what conditions the second alternative would become preferable.

In other words, the DSS value of this model lies not only in the fact that it produced a single ranking list, but in the fact that it showed the logic behind that ranking list and made it possible to examine the consequences of changing priorities.

Table 4. Supplier Selection Decision Matrix

Supplier	Price (BAM)	Quality	Support	Delivery time (days)
TechSol	50.000	9	5	15
GlobalIT	42.000	7	3	10
EcoData	47.000	8	4	20

Table 5. Normalized criteria values

Supplier	Price	Quality	Support	Delivery time
TechSol	0,8400	1,0000	1,0000	0,6667
GlobalIT	1,0000	0,7778	0,6000	1,0000
EcoData	0,8936	0,8889	0,8000	0,5000

Table 6. Scores and ranks in the baseline scenario

Supplier	Overall score	Rank
TechSol	0,9027	1
GlobalIT	0,8533	2
EcoData	0,8341	3

Table 7. Rescaled weights in the scenario of increased price importance

Criterion	New weight
Price	0,6000
Quality	0,2000
Support	0,1333
Delivery Time	0,0667

Table 8. Scores and ranks in the scenario of increased importance of price

Supplier	Overall score	Rank
GlobalIT	0,9022	1
TechSol	0,8818	2
EcoData	0,8539	3

5. Discussion

5.1. Interpretation of the findings in the context of DSS logic

The obtained findings confirm one of the basic assumptions of the DSS approach: the quality of the decision does not only result from "accurate data", but also from transparent modeling of preferences. In the basic scenario, TechSol is the best choice because, despite the limited budget, the organization still places importance on quality and support. When, however, priorities shift towards more aggressive cost discipline, the priority shifts to GlobalIT. This means that the "optimal" decision cannot be interpreted outside of the system of assumptions from which it derived.

This is exactly where the maturity of the DSS approach is reflected. Instead of offering the user the illusion of absolute objectivity, the model explicitly shows the dependence of results on managerial priorities. By doing so, the DSS does not eliminate the need for judgment; Rather, it structures judgment, making it visible and verifiable. Such an approach is especially important in organizations where decisions must be explained to management, audit, procurement committees, or other stakeholders.

5.2. Excel as a "lightweight" DSS platform

The practical significance of the paper also lies in the demonstration that Microsoft Excel can serve as a functional

lightweight DSS platform for many operational decisions. In small and medium-sized businesses, as well as institutions with limited budgets for specialized software, Excel is often the only realistically available analytics environment. Its value is not that it can replace enterprise BI or advanced MCDM platforms, but that it enables a fast, understandable and easily adaptable decision-making model.

Microsoft's support for What-If Analysis, Scenario Manager, and Solver further confirms that Excel is not only a tabular calculation tool, but also an environment suitable for simulation, scenario comparison, and optimization. When such functionality is combined with good model thinking, it is possible to build solutions that are robust enough for everyday business practice, with an acceptable level of complexity and cost.

However, Excel's affordability also comes at a price. Powell, Baker and Lawson warn that errors in spreadsheet models are common and can produce serious consequences for the quality of decisions. In the DSS context, this means that the transparency of the formula is not sufficient on its own; verification protocols, test values, control cells, cross-auditing, and documentation of assumptions are also required.

5.3. Position of the paper in relation to the MCDM literature

The chosen SAW/WSM method is not the most sophisticated among MCDM approaches, but it is a rational choice for the aim of the paper. In theoretical terms, SAW starts from linear compensation between criteria: a high value of one criterion can compensate for a weaker value of another. This is both a strength and a limitation. The strength is in simplicity and clarity. The limitation is that some real problems may require non-linear relationships, acceptance thresholds, or partial ranking of alternatives.

In future expansions of the research, it would be benefit to compare the results of the SAW model with the TOPSIS, VIKOR or AHP methods. Such a comparison could show whether the supplier ranking is maintained even when the method is changed, i.e. whether the result is methodologically robust. However, for the purpose of this paper, which aims to demonstrate an accessible and easy-to-understand DSS implementation, SAW remains an adequate and practically justified method.

5.4. The role of generative AI: benefits and limits

In this paper, generative artificial intelligence is not a source of decision, but a tool for accelerating certain phases of the analytical process. Its Benefitness is evident in a number of points. First, it can help the user formulate or understand Excel formulas faster. Secondly, it can facilitate the textual explanation of the results and scenarios obtained. Third, it can serve as an interactive assistant in structuring problems and identifying additional questions to consider.

Empirical work on the effects of generative AI shows that this kind of support can indeed increase productivity in knowledge work tasks, but also that the effects are not the same for all tasks and all users. Brynjolfsson, Li and Raymond find in QJE an increase in productivity with significant heterogeneity of effects, while Dell'Acqua and colleagues conceptualize a "jagged technological frontier", i.e. the uneven effect of AI assistance even within similar knowledge-intensive tasks. In the context of DSS, this means that

generative AI can be very Benefit for auxiliary, explanatory and routine analytical actions, but not as an unconditionally reliable source of final evaluation.

A key limit stems from the LLM system's tendency to hallucinations. If generative AI invents a literature source, misinterprets a result, or offers a convincing but inaccurate explanation, the user can make a bad decision without additional verification. That is why a human-in-the-loop approach is necessary in the DSS environment: a human remains responsible for defining the problem, selecting criteria, verifying the data, validating the model, and finally interpreting the results.

5.5. Transparency, accountability and risk management

The contemporary recommendations of NIST, UNESCO and ICMJE are of particular relevance to this topic, although they come from different institutional contexts. NIST AI RMF emphasizes the need for AI systems to be assessed through the prism of risk, reliability, transparency, and negative consequence management. UNESCO insists on the human-centric use of generative AI and the development of institutional policies that protect the quality and integrity of work. ICMJE specifically reminds that AI tools cannot bear copyright or ethical responsibility for published content.

Translated into DSS practice, this means that organizations should not adopt generative AI as a substitute for decision-making, but as a support that must be embedded in a controlled process. Such a process should include:

- clear records of where AI has been used,
- verification of all numerical and bibliographic elements,
- documentation of input data and the weight of criteria,
- the ability to audit models and reconstruct results,
- training users to distinguish an auxiliary suggestion from a verified fact.

5.6. Limitations of the study

This work has multiple limitations that need to be openly acknowledged. First, the case study includes only three alternatives and four criteria, so it does not pretend to be the complexity of real large-scale procurement systems. Second, the weights of the criteria were taken as starting preferences and were not empirically determined through a broader procedure, such as the AHP pair comparison. Third, the study uses structured and predefined data; the model does not include the automatic processing of unstructured information, such as text reviews, supplier news, or ESG reports. Fourth, although generative AI is conceptually integrated as an auxiliary layer, the work does not involve experimental measurement of how much it actually saves time or improves user understanding.

Nevertheless, these limitations do not diminish the core value of the work. On the contrary, they precisely define its scope: it is a methodologically transparent demonstration of an operational DSS approach, not a large-scale experimental study. It is precisely because of this clarity of work that its practical applicability remains high.

5.7. Managerial implications for small and medium-sized enterprises

One of the most important practical contributions of the paper is its relevance to small and medium-sized enterprises. It is in these organizations that there is often a need for better decision-making, but not enough resources for expensive BI platforms, specialized MCDM tools or teams of data analysts. The presented model shows that a better approach to decision-making does not necessarily require high investments, but disciplined work with criteria, data and model assumptions.

For the SME sector, it is especially important that Excel enables the rapid creation of "working" models that can be adapted to a specific problem: supplier selection, investment option selection, candidate assessment, project prioritization, or allocation of limited resources. When generative AI is used in addition to helping with formulas and explanations, even users with more modest technical knowledge can come up with a functional DSS framework. However, this does not mean that the process is trivial. On the contrary, the greater availability of tools also increases the need for rules for their use.

Therefore, SMEs should adopt at least three organizational routines. The first is a record of assumptions: where the data came from, how the criteria were defined, and why these weights were used. The second is a routine sensitivity analysis: at least one to two alternative priority scenarios should be examined before a decision is taken. The third is the revision of the model by another person. These three routines are relatively inexpensive, and they significantly raise the reliability of the model.

5.8. The relationship between model simplicity and decision quality

A common dilemma in analytical practice is: is a more complex model better or a simpler model that the user really understands? The paper implicitly advocates the view that for a large number of operational decisions, greater complexity does not automatically mean greater practical Benefit. A model that the user does not understand, cannot explain and does not know how to revise is often less valuable than a simpler model that is completely transparent.

This does not mean that advanced methods should be abandoned. On the contrary, in more complex and strategically important situations, more sophisticated approaches may be necessary. However, the principle of model proportionality also applies to organizational needs: analytical complexity should correspond to the complexity of the problem, the significance of the decision, and the capacities of the user. In this sense, SAW/WSM in Excel is a good example of methodological moderation – it is structured enough to support a rational decision, but simple enough to remain auditable.

5.9. Comparison of SAW Approaches with Alternative Methods

To fully understand the range of the presented model, it is Benefit to briefly compare SAW with some other common MCDM methods. AHP is very Benefit when it is necessary to systematically determine the weights of criteria through pair comparisons and include expert consistency assessment. TOPSIS is appropriate when one wants to assess how close each alternative is

to the ideal and far from the anti-ideal solution. VIKOR is relevant in situations where a compromise solution is sought between several opposing goals. PROMETHEE and ELECTRE may be Benefit when simple linear compensation is not desirable and when partial dominances or indifference thresholds need to be considered.

Compared to these approaches, SAW has two key advantages: *minimal implementation complexity and high interpretive clarity*. Its main drawback is the assumption of full compensation among the criteria. In practice, this means that a very high value of one criterion can be "paid" for by a weaker value of another, although such an exchange is sometimes not acceptable in real life. For example, an extremely low price should not always compensate for serious shortcomings in the reliability of suppliers. Therefore, future extensions of the model may include minimum acceptance thresholds for individual criteria, thus combining the SAW approach with simple exclusion logic.

6. Recommendations for Practice and Future Research

Based on the theoretical insights and the results of the case study, it is possible to formulate several recommendations for practice.

First, organizations that use Excel for business decisions should formalize a minimal DSS protocol. This entails clearly defining criteria, documenting weights, storing original data, separate cells for parameters, control cells for checking aggregate weights, and mandatory sensitivity analysis before making a final decision.

Second, in cases where generative AI is used, the rule should be adopted that AI can assist in formulation, explanation, and summarization, but must not be the sole source of facts, formulas, or recommendations. Everything that AI generates must be verified through real data, an Excel model, and verified literature.

Third, it is recommended that organizations develop simple guidelines for spreadsheet auditing. This can include: double-checking formulas, key cell locking, model versioning, peer review, and standardized templates for repeatable decisions.

Fourth, when it comes to purchasing decisions, it is Benefit to gradually expand the model with additional criteria such as supply chain reliability, experience of previous cooperation, warranty terms, environmental standards and total cost of ownership. This would result in a more realistic and strategically relevant model.

For future research, four directions are particularly interesting. The first is a methodological comparison of the SAW model with other MCDM methods on the same data set. The second is to include more vendors and criteria to test the scalability of an Excel implementation. The third is an experimental examination of the actual effect of generative AI on the speed, quality and comprehensibility of business analyses. The fourth is the development of a hybrid model in which structured Excel data would be linked to AI analysis of unstructured text sources, but under strict verification rules.

6.1. Proposed operational protocol for organizations

Based on the findings of the paper, a simple operating protocol can be proposed for organizations that want to use Excel and generative artificial intelligence in the DSS environment:

Step 1: Define the decision, alternatives, and criteria.

Step 2: Separate the cost and Benefit criteria.

Step 3: Document the sources of all input data.

Step 4: Set the weights of the criteria explicitly and justify them.

Step 5: Establish control cells to check the sum of weights and the correctness of the formulas.

Step 6: Implement at least one baseline and one alternative scenario.

Step 7: If AI is used, record at what stages it was used and why.

Step 8: Have the final result reviewed by another person before making a formal decision.

Such a protocol is simple enough to be applicable in practice, and at the same time serious enough to reduce the most common risks of working with spreadsheet models and generative AI support.

6.2. Possibilities for methodological extension

Further improvement of the model can go in several directions. One direction is to introduce a procedure for structured weight determination, for example through the AHP or Delphi approach. The second direction is to include more criteria and alternative data sources. The third direction is to connect Excel models to external sources, including ERP or BI reports, to reduce manual data manipulation and improve the timeliness of the model. The fourth direction is the development of hybrid solutions in which generative AI would also help in the processing of unstructured text sources, but through clearly defined validation steps.

In this way, future work could move from a demonstration model to more complex, organizationally integrated DSS frameworks. However, the basic message remains the same: regardless of the level of technological complexity, the quality of decision-making still depends on the clarity of the criteria, the verifiability of the data, and the responsibility of the people who use the model.

7. Conclusion

The paper showed that decision support systems based on multi-criteria analysis can be successfully implemented in a simple, widely available tool such as Microsoft Excel. By using the SAW/WSM method, clear normalization of criteria, weighting and sensitivity analysis, it is possible to build a model that is at the same time transparent, reproducible and practically applicable in an organizational context.

A case study of supplier rankings confirmed that the choice of alternative depends on explicitly defined priorities. In the basic scenario, TechSol is the most advantageous due to the combination of high quality and excellent technical support. However, when the price criterion becomes more dominant, GlobalIT takes the lead. This finding is methodologically important because it shows that sensitivity analysis is not a secondary activity, but an integral part of a serious DSS approach. Without it, the user could get the wrong impression that one alternative is permanently the best, although it actually depends on a change in managerial priorities.

The paper also showed that generative AI can have a Benefit, but strictly ancillary role in BI/DSS work. It can speed up the formulation and understanding of Excel models, help interpret results, and reduce the cognitive burden on users. Nevertheless, due to the risk of hallucinations, superficial generalizations, and inaccurate references, generative AI should not be treated as an autonomous authority. The reliability of the DSS model still depends on the quality of the input data, the verification of formulas, the documentation of assumptions, and the human responsibility for the final decision.

The greatest value of the presented approach lies in its combination of accessibility and transparency. In environments that do not have access to expensive specialized platforms, an Excel-based MCDM DSS can be an efficient and realistic solution to support operational and tactical decisions. When such a model is complemented by the responsible use of generative AI, organizations get a tool that is not a substitute for managerial judgment, but its reinforcement – provided that verification, auditability and awareness of the limitations of technology remain present.

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