UDC 005.311:004
JEL classification: M10, D81, D83

CRITERIA FOR DIGITAL ANALYTICAL INFORMATION SUITABILITY IN MANAGERIAL DECISIONS

KAPUSTIAN Iryna
National University "Odesa Law Academy"
https://orcid.org/0000-0002-4915-7864
e-mail: kapustyanirene@onua.edu.ua

The purpose of the article is to theoretically substantiate a system of criteria for assessing the suitability of digital analytical information for specific managerial decisions. The research employs comparative analysis of scientific approaches, conceptual modelling, logical deduction and scenario analysis using hypothetical numerical data. General data quality, information suitability for a task and managerial decision performance are distinguished. Information requirements are derived from the available courses of action, intended outcome, planning horizon, decision deadline, opportunities to revise the decision and losses associated with errors. Universal requirements for information transparency are separated from task-dependent criteria for information sufficiency. A matrix linking the criteria to four tasks is developed: inventory replenishment, marketing budget allocation, investment project selection and an operational response to supply disruption. The matrix specifies the required timeliness, granularity, scope, accuracy, explainability and stability of analytical conclusions. The scientific contribution consists in aligning these criteria with task characteristics and with a procedure for examining whether information limitations can reverse the preference between alternatives. A numerical example shows that highly accurate individual indicators do not necessarily justify a choice and that uncertainty does not always require postponing action. The example examines a rule that minimizes the maximum loss in expected benefit and identifies an upper bound on the potential benefit of obtaining more precise information. Information gaps are assessed in terms of their influence on the choice, the cost of obtaining additional information and the consequences of delaying the decision. The practical significance lies in using the matrix to prepare analytical assignments, review management reports and document the limitations of recommendations without developing a new software product. The study is theoretical; the calculations illustrate the logic of the approach and are not based on observations of enterprises. Conditions for revising information requirements following changes in objectives or available courses of action are specified. Future research should empirically examine agreement between evaluators in applying the criteria, measure information acquisition and decision delay costs, and investigate changes in choices under different characteristics of decision-support information.

Keywords: management, digital analytics, information quality, managerial decisions, uncertainty, information criteria, sensitivity analysis.

https://doi.org/10.31891/mdes/2026-22-46

Стаття надійшла до редакції / Received 01.10.2026
Прийнята до друку / Accepted 29.10.2026
Опубліковано / Published 12.11.2026

This is an Open Access article distributed under the terms of the Creative Commons CC-BY 4.0

© KAPUSTIAN Iryna

INTRODUCTION

Digital analytical systems provide managers with metrics, forecasts, and recommendations for decision-making. However, the fact that a metric is calculated correctly does not necessarily mean it is sufficient for selecting a specific course of action. The information may pertain to a different time period, level of detail, or set of entities than those relevant to the decision at hand. For instance, average monthly sales volume might be suitable for general planning but insufficient for the daily replenishment of an individual stock-keeping unit (SKU). This gives rise to the challenge of ensuring that analytical information aligns with the nature of the specific management task.

Information requirements vary depending on the objective, the timeframe for the decision, the consequences of potential errors, and the feasibility of revising the decision later. In the context of long-term investment, the validity of forecasting assumptions and the robustness of a project's advantages across various scenarios are critical. Conversely, when responding to supply disruptions, the timeliness of data and the potential consequences of delayed action become paramount. In practice, the task involves identifying the specific information characteristics required for a given decision and determining whether further refinement of that information is warranted. From a research perspective, the task entails aligning criteria for information sufficiency with the structure of available alternatives, potential losses, and the costs associated with acquiring the information.

ANALYSIS OF RECENT RESEARCH AND PUBLICATIONS

The theoretical foundation of this study rests on the concept that data quality is multidimensional and that its assessment depends on the needs of the user [1]. Contemporary research systematizes methods for incorporating context into data quality management and confirms the necessity of defining information requirements based on the specific conditions of use [2]. These approaches allow for viewing the suitability

of information as its alignment with a specific task—a concept that requires further specification to guide managerial decision-making.

Ukrainian literature explores the potential of business analytics, as well as the challenges associated with integrating big data into enterprise operations [3]. Research into the methodological foundations of business analysis underscores the need to define information requirements at the outset of analytical work, align evaluation criteria, and standardize metrics [4]. This approach establishes a basis for setting requirements for analytical outputs before they are utilized by managers.

A study focusing on digital innovations in support of strategic management decisions proposes a model that integrates crisis-related constraints, information infrastructure, analytics, and the selection and monitoring of outcomes for marketing startup projects [5]. This model centers on the organization of a strategic management support system. The present article further develops these concepts by focusing on the assessment of the information base underlying specific decisions.

The organizational prerequisites for data utilization are examined through the lens of an enterprise's analytical culture [6] and the quality of its internal information [7]. Prescriptive analytics and decision-aware model training link forecasting with the selection of actions and the assessment of losses resulting from errors [8; 9]. The theory of the value of information provides a rationale for evaluating additional data based on its potential to improve decision-making [10]. These concepts form the basis for determining whether refining information can alter a managerial choice and whether the expected improvement justifies the costs incurred to obtain that information.

A distinct body of research focuses on the use of algorithmic recommendations. This includes the division of authority between a manager and a system [11], the dependence of human-AI interaction outcomes on the specific task at hand [12], and the evaluation of explanations and their impact on the user [13; 14]. Consequently, it is necessary to verify that a recommendation aligns with managerial objectives and to distinguish between the clarity of an explanation and the soundness of the proposed action. Approaches to evaluating data-driven decisions also encompass process analysis and feedback following the implementation of a decision [15].

IDENTIFICATION OF PREVIOUSLY UNRESOLVED ASPECTS OF THE OVERALL PROBLEM

The approaches examined encompass data quality, the organizational context of analytical activities, the optimization of selection processes, and the evaluation of outcomes. Further specification is required regarding how these elements are integrated into the procedure for verifying information prior to making a specific management decision. In particular, it is necessary to determine how the characteristics of a task dictate information requirements, what evidence confirms the sufficiency of that information, and under what conditions an identified constraint might alter the preference between available alternatives.

In this article, this issue is explored by constructing a matrix that aligns information criteria with four types of management tasks, and by defining the procedure for its application. The proposed approach integrates the task profile, the evidence required to establish information sufficiency, an assessment of how constraints affect decision-making, and an evaluation of whether further refinement is warranted. This enables the prioritization of additional analytical work, taking into account management implications, the cost of verification, and the timeframe for obtaining results.

RESEARCH AIM AND METHODOLOGY

The objective is to provide a theoretical substantiation for a system of criteria determining the suitability of digital analytical information for specific management decisions. The study employs a comparative analysis of purposefully selected publications from 2023–2026 alongside three foundational works from earlier periods, utilizing conceptual modeling and logical deduction. The sources are compared based on the subject of assessment, the decision-making stage, and the method of accounting for the specific task. This selection does not constitute an exhaustive systematic review. A scenario analysis is conducted using hypothetical numerical data; this serves to verify the logic of the procedure rather than its empirical effectiveness. The documentation of limitations and authority aligns with the principles of AI risk management [16].

PRESENTATION OF THE MAIN BODY OF THE RESEARCH

Digital analytical information consists of metrics, forecasts, explanations, and recommendations derived from data processing within a digital environment. Its suitability is defined by whether it is sufficient to compare specific alternatives against an agreed-upon objective within a set timeframe. Data quality characterizes the information product itself; suitability refers to its alignment with the task at hand;

and the effectiveness of a decision relates to the outcomes of the action taken. A positive outcome does not negate an initial deficiency in the information, just as the realization of an anticipated adverse scenario does not prove that the information was unsuitable.

The foundational document is the task passport, which outlines the objective, available alternatives, the unit of action, the time horizon for consequences, the deadline for making a choice, the scope for cancellation or revision, and the potential losses resulting from errors. For example, for the model problem below, the passport records choice A or B for one period, net benefit estimate, demand probability range 0.35–0.65, and one-time refinement cost 4 conventional units. The record must also identify the manager in charge, the report version, and any revision events; these fields ensure the reproducibility of the informational basis for the decision.

Universal requirements apply to all tasks; however, the depth of their substantiation depends on the consequences of the decision. These requirements encompass provenance, semantic definiteness — the unambiguous meaning of an indicator — and the transparency of constraints. Task-specific criteria are presented in Table 1. Scope is distinguished from transferability: the former relates to the representation of relevant objects, while the latter concerns the applicability of a conclusion to target conditions. The robustness of a preference implies that the chosen alternative remains valid even when initial assumptions undergo permissible changes.

Evidence serves as the basis for assessment, while a criterion represents a specific property being verified. These should not be replaced by an arbitrary aggregate score. Permissible deviations are established prior to analysis, based on their potential consequences—such as shortfalls, cost overruns, loss of benefits, or expiration of validity periods. To ensure explainability, the intended use of the conclusion and the verifiable assumptions must be documented; however, a clear verbal explanation is not a substitute for substantiating a causal effect. If a quantitative limit is unknown, the relevant professional judgment should be documented rather than an arbitrary indicator of precision.

Table 1.

Criteria and indicators of information sufficiency

Criterion	Evidence to Check	Assessment Rule
Provenance (Universal)	Source, time of generation, model version, or transformation	The origin of the result can be established
Semantic definite-ness (Universal)	Definitions, units, basis of comparison, aggregation rules	The meaning of the indicator is consistent with the decision objective
Transparency of limitations (Universal)	Assumptions, missing data, uncertainty ranges	Material limitations are explicitly documented
Timeliness	Observation dates, rate of change, validity period	Information is available before the opportunity to choose is lost
Granularity	Unit of analysis and unit of management action	Aggregation does not conceal differences that would change the action
Scope	Represented objects, segments, and scenarios	Missing data that could change the preferred alternative have been checked
Transferability	Comparison of source and target conditions	Differences are accounted for, or the scope of applicability is restricted
Accuracy adjusted for losses	Error range and consequences of errors in different directions	Errors are assessed against the agreed acceptable loss
Explanatory adequacy	Forecast boundaries; basis for conclusions about causal effects	For forecasts, conditions of applicability are disclosed; for interventions, causal assumptions are justified
Robustness of preference	Thresholds at which the preferred alternative changes and sensitivity analysis results	The choice remains stable, or any potential loss from a change is acceptable under a defined rule

Source: author's own work.

Four tasks have been selected to compare information requirements across operational forecasting, changes in managerial action, long-term commitments, and urgent responses. They differ in their planning horizons, decision deadlines, consequences of error, and opportunities to revise an action after implementation. The matrix in Table 2 translates these differences into task-specific assessment requirements. It identifies what should be examined under each criterion and what evidence can support

the use of information in a particular decision. The matrix does not assign a universal level of importance to the criteria, since their significance depends on the objectives and constraints of the task. For example, timeliness becomes particularly important when a delay would remove an available course of action, whereas the sensitivity of projected benefits requires closer attention when a decision creates substantial irreversible commitments. Across all four tasks, the data sources, indicator definitions, calculation methods, and limitations must be specified. These common requirements provide a consistent basis for assessment, while the remaining requirements are adapted to the circumstances of the decision.

Regarding inventory, precise sales records may fail to capture unmet demand resulting from stockouts. In marketing, the correlation between advertising and sales might simply reflect seasonality; it does not prove that an increased budget yields incremental gains. For investments, it is necessary to determine which shifts in cash flows alter the ranking of projects and whether a phased commitment is feasible. Conversely, in the event of supply disruptions, a delay in verification could eliminate the opportunity to secure a resource. These distinctions determine what evidence must be obtained before taking a specific action.

Table 2.

Alignment of criteria with the management task

Criterion	Inventory Replenishment	Marketing Budget	Investment Project	Disruption Response
Timeliness	Order cycle, deli-very lead time	Customer response period, seasonality	Cash flow horizon	Update before the op-portunity to act is lost
Granularity	Product, ware-house, period	Channel, segment, incremental margin	Project, stage, cash flow	Failure point, available resource
Scope	Shortages and unmet demand	Material target segments	Demand and cost scenarios	Critical dependencies and reserves
Transfer-ability	Changes in product range and season	Transfer of effects to a new segment	Relevance of comparable projects to project conditions	Relevance of pre-vious disruptions to the current situation
Accuracy and losses	Consequences of overstocking and shortages	Error in incre-mental margin estimates	Range of cash flows near the decision threshold	False alarm and missed disruption
Explanatory adequacy	Demand forecast limitations	Evidence of budget impact	Cash flow assumptions	Rationale for a speci-fic response measure
Robustness of preference	Change in order quantity	Change in channel preference	Change in project ranking	Reversal of a reversible measure

Source: author's own work.

The procedure consists of six steps. The first is the approval of the task specification and the preference criterion. A recommendation to maximize sales, for instance, does not automatically apply to a task focused on maintaining liquidity.

The second step involves creating an information profile: for each criterion, the required evidence, permissible deviation, and the person responsible are defined. The third step entails comparing requirements against existing reports and documenting any constraints. For every gap, it is noted whether it affects the potential benefit, the availability of an alternative, or the timeline for its implementation. An unknown value is not equated to having zero impact.

The fourth step is sensitivity analysis—checking whether the chosen option changes when underlying assumptions are varied. The ranges for these variations are justified based on known margins of error, historical observations, or scenario-based assumptions. The fifth step involves weighing the potential value of further refinement against its cost and the consequences of any resulting delay. In the absence of a probability distribution, upper bound on the potential benefit or a qualitative rationale is provided, rather than a fabricated "expected value."

The sixth step is the documentation of the chosen option, the specific version of the data used, any remaining constraints, and the review event. This summary is recorded in the format: "constraint — potential impact — action taken — condition for re-evaluation." The analyst validates the data characteristics, the manager approves the objective and the acceptable level of loss, and the system manages

version control and performs calculations. This framework also applies to recommendations generated by AI.

The hypothetical problem involves choosing between two options, A and B, for a single period. The objective is to obtain the expected net benefit; both high and low demand scenarios are considered. The benefits already account for implementation costs; no other objectives, states, or alternatives are included. The probability of high demand is an unknown parameter. The input values and results are presented in Table 3.

Table 3.

Estimated benefits and sensitivity analysis results

Indicator	Option A	Option B
Net benefit under high demand, in conventional units	100	70
Net benefit under low demand, in conventional units	60	80
Expected net benefit at a probability of 0.50	80	75
Expected net benefit at a probability of 0.35	74	76,5
Expected net benefit at a probability of 0.65	86	73,5
Maximum loss of expected net benefit in the 0.35–0.65 range	2,5	12,5

Source: author's own work.

At a probability of 0.50, Option A yields 80 units, while Option B yields 75 units. For Option A, the expected net benefit is 60 plus 40 multiplied by the probability of high demand; for Option B, it is 80 minus 10 multiplied by the same probability. Equality is reached at a probability of 0.40, where both outcomes equal 76. Therefore, the assessment of accuracy should focus on the likelihood of crossing this threshold.

The initial range of 0.35–0.65 is a scenario-based assumption rather than a statistical confidence interval. At the lower bound, Option B outperforms Option A by 2.5 units, while at the upper bound, Option A outperforms Option B by 12.5 units. When the probability is unknown, a manager might adopt a decision rule to minimize the maximum potential loss in expected net benefit. Here, "loss" is defined as the difference between the expected net benefit of the best available option and that of the chosen option, given a specific probability value; it does not refer to the loss incurred under a specific realized state of demand. Comparing the maximum losses — 2.5 versus 12.5 — favors Option A.

Once the range is refined to 0.52–0.60, Option A's advantage becomes 6–10 units, persisting across all values within this range. However, if the net benefit for Option A under low-demand conditions decreases from 60 to 50 — while all other factors remain constant — the threshold of equality shifts from 0.40 to 0.50. Thus, the adequacy of a given probability estimate depends on the structure of the net benefits. In the initial range, precise knowledge of the probability can improve the expected net benefit — compared to choosing option A immediately — by no more than 2.5 units for any given value of the parameter. Therefore, a one-time refinement costing 4 units cannot be justified solely by the improvement to this choice. This represents the upper limit of the potential benefit derived from knowing the parameter, rather than the expected value of a specific study or of having advance knowledge of future demand. This conclusion assumes that net benefits remain constant, no new alternatives emerge, and the information is not reused.

The scientific novelty lies in the specification of the evaluation procedure through the following linkage: "task profile — criterion — evidence — impact of a constraint — method of information utilization." Its concrete output is a matrix designed for four types of management tasks. Unlike a mere characterization of data set properties, this verification process culminates in a conclusion regarding the feasibility of a specific course of action. At the same time, contextual evaluation, sensitivity analysis, and the assessment of the value of information serve as theoretical foundations rather than as new findings of this work.

Additional information may refine the description of a situation without necessarily altering the decision. Therefore, the priority for seeking further clarification is determined by the potential impact on the choice made, as well as the cost-benefit ratio. In practice, the matrix can be incorporated into the requirements for an analytical report, while the documentation of constraints can be included in a manager's explanatory note. Software implementation is not required for initial application.

Based on the proposed procedure, a rule for prioritizing information refinements has been formulated. For each identified constraint, it is necessary to determine which alternative's evaluation is affected, the range of permissible deviations that could trigger a revision of the choice, and the associated loss of expected benefit. Priority should be given to refining information where uncertainty could lead to a change in the chosen course of action or cause the loss to exceed the agreed-upon threshold. If an alternative remains superior across the entire plausible range of values, then—all other factors being equal—refining the corresponding metric is of lower priority. This assessment takes into account the cost of verification, the time required to obtain results, and the feasibility of revising the decision. Applying the rule entails examining the combined impact of interdependent constraints, as evaluating them individually might mask shifts in decision-making. This approach utilizes a matrix to allocate analytical effort across various information gaps, prioritized according to their managerial implications.

The limitations of this approach stem from the lack of empirical validation within enterprises, an incomplete set of tasks, and the fact that acceptable loss thresholds depend on managerial judgment. Stability within a defined range does not guarantee stability outside of it, nor does the method reveal overlooked alternatives. For further verification, it is advisable to compare independent assessments made by managers—using consistent criteria—while also analyzing shifts in choices, losses relative to an established benchmark, and the time invested in refining the analysis.

CONCLUSIONS

A system for evaluating the suitability of digital analytical information has been developed, linking universal requirements and task-specific criteria with the necessary evidence and the implications of information limitations. A matrix details the verification process for applications such as inventory replenishment, marketing budget allocation, investment selection, and response to disruptions.

A prioritization rule for information refinement has been formulated; it determines the sequence for addressing limitations, taking into account the feasibility of altering a choice, the acceptable loss, the cost of verification, and the time required to obtain additional data.

A model-based calculation demonstrates the threshold for changing an alternative, allowing for the separation of the potential benefit of refinement from its associated cost. This approach is suitable for structuring the preparation of analytical reports and documenting the rationale behind management decisions. Future research should assess the consistency of applying these criteria, the utility of the procedure, and the costs involved in its implementation within real-world processes.

REFERENCES:

1. Wang, R. Y., & Strong, D. M. (2015). Beyond accuracy: What data quality means to data consumers. *Journal of Management Information Systems, 12*(4), 5–33. DOI: https://doi.org/10.1080/07421222.1996.11518099

2. Serra, F., Peralta, V., Marotta, A., & Marcel, P. (2024). Use of context in data quality management: A systematic literature review. *Journal of Data and Information Quality, 16*(3), Article 19. DOI: https://doi.org/10.1145/3672082

3. Dvulit, Z. P., & Maznyk, L. V. (2024). The role of business analytics in the era of Big Data: New opportunities for managerial decision-making. *Management and Entrepreneurship in Ukraine: The Stages of Formation and Problems of Development*, 6(2), 152–165. DOI: https://doi.org/10.23939/smeu2024.02.152 (in Ukrainian).

4. Ionin, Ye. Ye. (2024). The international business analysis standard: A theoretical and methodological basis for substantiating managerial decisions. *Economics and Organization of Management*, 1(53), 40–50. DOI: https://doi.org/10.31558/2307-2318.2024.1.4 (in Ukrainian).

5. Kotlubai, V. O., Kapustian, I. V., & Redina, Ye. V. (2026). Digital innovations in information systems for supporting strategic managerial decision-making as a factor in changing the economic efficiency of marketing start-up projects under crisis conditions. *Current Problems of Sustainable Development*, 3(3), 161–169. DOI: https://doi.org/10.60022/3(3)-19S (in Ukrainian).

6. Szukits, Á., & Móricz, P. (2024). Towards data-driven decision making: The role of analytical culture and centralization efforts. *Review of Managerial Science, 18*(10), 2849–2887. DOI: https://doi.org/10.1007/s11846-023-00694-1

7. Lem, K. W. (2024). Data analytics strategy and internal information quality. *Contemporary Accounting Research, 41*(2), 1376–1410. DOI: https://doi.org/10.1111/1911-3846.12942

8. Bertsimas, D., & Kallus, N. (2020). From predictive to prescriptive analytics. *Management Science, 66*(3), 1025–1044. DOI: https://doi.org/10.1287/mnsc.2018.3253

9. Mandi, J., Kotary, J., Berden, S., Mulamba, M., Bucarey, V., Guns, T., & Fioretto, F. (2024). Decision-focused learning: Foundations, state of the art, benchmark and future opportunities. *Journal of Artificial Intelligence Research, 80*, 1623–1701. DOI: https://doi.org/10.1613/jair.1.15320

10. Howard, R. A. (1966). Information value theory. *IEEE Transactions on Systems Science and Cybernetics, SSC-2*(1), 22–26. URL: https://ui.adsabs.harvard.edu/abs/1966ITSSC...2...22H/abstract

11. Kim, H., Glaeser, E. L., Hillis, A., Kominers, S. D., & Luca, M. (2024). Decision authority and the returns to algorithms. *Strategic Management Journal, 45*(4), 619–648. DOI: https://doi.org/10.1002/smj.3569

12. Vaccaro, M., Almaatouq, A., & Malone, T. (2024). When combinations of humans and AI are useful: A systematic review and meta-analysis. *Nature Human Behaviour, 8*(12), 2293–2303. DOI: https://doi.org/10.1038/s41562-024-02024-1

13. Kim, J., Maathuis, H., & Sent, D. (2024). Human-centered evaluation of explainable AI applications: A systematic review. *Frontiers in Artificial Intelligence, 7*, Article 1456486. DOI: https://doi.org/10.3389/frai.2024.1456486

14. Reinhard, P., Li, M. M., Peters, C., & Leimeister, J. M. (2026). Effects of explanations in human-AI interaction: A systematic review and framework for future research on explainable AI. *Information Systems Frontiers, 28*(3), 1233–1266. DOI: https://doi.org/10.1007/s10796-026-10716-4

15. Elgendy, N., Päivärinta, T., Elragal, A., Hannula, K., & Puolitaival, K. (2024). Design principles for data-driven decision evaluation. *Procedia Computer Science, 239*, 563–574. DOI: https://doi.org/10.1016/j.procs.2024.06.208

16.*Artificial intelligence risk management framework (AI RMF 1.0)* (NIST AI 100-1). (2023). National Institute of Standards and Technology. DOI: https://doi.org/10.6028/NIST.AI.100-1

КРИТЕРІЇ ПРИДАТНОСТІ ЦИФРОВОЇ АНАЛІТИЧНОЇ ІНФОРМАЦІЇ ДЛЯ УПРАВЛІНСЬКИХ РІШЕНЬ

КАПУСТЯН Ірина
Національний університет «Одеська юридична академія»

Метою статті є теоретичне обґрунтування системи критеріїв придатності цифрової аналітичної інформації для конкретних управлінських рішень. Застосовано порівняльний аналіз наукових підходів, концептуальне моделювання, логічну дедукцію та сценарний аналіз на умовних числових даних. Розмежовано загальну якість даних, придатність інформації до завдання та результативність управлінського рішення. Запропоновано визначати інформаційні вимоги через альтернативи дії, цільовий результат, часовий горизонт, строк вибору, можливість перегляду рішення та втрати від помилок. Виокремлено універсальні вимоги до прозорості інформації та ситуаційно залежні критерії її достатності. Розроблено матрицю відповідності критеріїв чотирьом завданням: поповненню запасів, розподілу маркетингового бюджету, вибору інвестиційного проєкту й оперативному реагуванню на перебої постачання. Матриця конкретизує потрібну актуальність, деталізацію, охоплення, точність, пояснюваність і стійкість висновків. Наукова новизна полягає в узгодженні цих критеріїв із характеристиками завдання та процедурою перевірки того, чи здатні інформаційні обмеження змінити перевагу між альтернативами. На модельному прикладі показано, що висока точність окремого показника не гарантує обґрунтованості вибору, а невизначеність не завжди потребує відкладення дії. Розглянуто застосування правила мінімізації найбільшої втрати очікуваної вигоди та визначено верхню межу можливої користі від додаткового уточнення інформації. Інформаційні прогалини запропоновано оцінювати з урахуванням їхнього впливу на вибір, вартості отримання додаткових відомостей і наслідків затримки рішення. Практична значущість полягає у можливості використання матриці для підготовки аналітичних завдань, перевірки управлінських звітів і документування обмежень рекомендацій без розроблення нового програмного продукту. Дослідження має теоретичний характер; наведені розрахунки ілюструють логіку підходу та не є результатами спостереження за підприємствами. Визначено умови перегляду інформаційних вимог у разі зміни цілей або альтернатив дії. Перспективами є емпірична перевірка узгодженості оцінок критеріїв, вимірювання витрат отримання інформації та затримки рішення, а також дослідження змін вибору за різних характеристик інформаційного забезпечення.

Ключові слова: менеджмент, цифрова аналітика, якість інформації, управлінські рішення, невизначеність, інформаційні критерії, аналіз чутливості.