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The value of expert judgments in decision support systems

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HIGHLIGHTS

- Three parts of DSS based on judgments are defined: information, quality, and algorithms.
- A systematic and quantitative assessment of the costs and benefits of DSSs.
- The introduction of a cost-benefit efficiency measure (the break-even point).
- Counterintuitively the results show that a less informative DSS can be more efficient.

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ABSTRACT

It is a challenge to improve a decision support system (DSS) based on expert judgments; the literature proposes to improve accuracy and performance by increasing the sophistication and complexity of the DSS, but at what cost? This study presents a model for encoding a DSS based on expert judgments and evaluating its efficiency, establishing a three-part analysis structure: information requirements (number of judgments), quality requirements (quality assurance mechanisms), and algorithmic complexity. With a focus on the cost of judgments, a systematic and quantitative coding of the performance and cost in each part of the DSS is established. A "break-even point" efficiency measure, defined as the maximum percentage of the optimal performance that can be paid per unit of resources, is proposed to ensure that the use of the DSS remains profitable. Counterintuitively, the results of a case study show that the efficiency of DSSs does not necessarily increase with respect to the informativeness level of DSSs. Overall, this study provides a new method for evaluating the efficiency of DSSs.

1. Introduction

Decision support systems (DSSs) are information systems designed to improve the decision-making process [1–3]. Intuition suggests that increasing the complexity of a DSS should improve its accuracy and performance, but does this improve its efficiency? Empirical evidence indicates that advances in technology increase the deployment of DSSs (IoT, ERP, big data) [4–6] in firms and governments for structured decisions [7], while DSSs based on judgments (for unstructured decisions) are maintained only in some large-scale projects [8]. This suggests that DSSs provide significant advantages in the efficient management of structured decisions, while their contributions to unstructured decisions have been questioned [9]. Therefore, the cost-efficiency of using a DSS in unstructured decisions and the cost-benefit balance of a DSS based on judgment of experts are topics worth investigating because the use of DSSs is not common in organizations [10–12]; this challenges their efficiency and raises important questions. Which elements of a DSS are most valuable? What are their costs? Can their incremental performance and cost be measured?

Efficiency quantifies the value of information and is defined as the difference between the reward that the decision-maker obtains in the absence of information and what can be obtained in its presence once the cost has been accounted for [13]. It is possible that some of the approaches proposed in the literature to improve the performance of DSSs (increasing the number of judgments, increasing the level of information of the judgments, etc.) may not be efficient due to the high costs they entail. This study aims to establish a model of the overall efficiency of different DSSs based on expert judgments, as well as to determine the contributions of the different parts of a DSS to its efficiency.

This paper proposes an analysis of a DSS based on three distinct structural parts: i) the systematic collection of information, integrating

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data from multiple sources (databases, internal information, expert judgments, etc.); ii) the establishment of mechanisms to ensure the quality of the collected information (reliability of the source, contradictions between data, coincidence between different sources, etc.); and iii) the processing of the information using algorithms (analytical and optimization models) to provide a DSS solution (a ranking among the alternatives or priority vectors of alternatives).

The model proposed in this paper is developed within the intentional bounded rationality (IBR) conceptual framework, where the existence of a probabilistic regularity in the judgments of experts permits one to establish a function between the performance of the alternatives and the level of error. This regularity allows a systematic and quantitative analysis of the performance and costs of each of the three structural parts described above. Thus, for a scenario for which the latent performances of the alternatives are known, the proposed model determines the error distribution of the judgments and the cost of the information, making the efficiency of each requirement introduced in the DSS quantifiable. Instead of specifying a set of judgments and assessing changes in the outcome rankings by modifying some of the parameters of the DSS (sensitivity analysis), the proposed approach evaluates a DSS in a counterfactual manner by examining all possible *combinations of judgments* that an expert can make.

The main contributions of this study are the following:

1) A three-part structure analysis of a DSS is proposed based on i) information requirements, ii) quality requirements, and iii) algorithms. This three-part decomposition will be shown with some outstanding DSSs.
2) The wide variety of judgments in different DSSs makes comparing them difficult. Thus, a general method for coding the three parts of a DSS for a systematic and quantitative assessment of its performance and cost is proposed.
3) A quantification of resource prices (expert judgments and algorithm complexity) is proposed.
4) The reference concept "profit of ignorance" is defined as the performance expectation obtained by making a random decision.
5) Based on the "profit of ignorance" and the expected performance of the analyzed DSS, a quantitative measure of the efficiency and cost-benefit balance (break-even point) is proposed.
6) The implementation of previous proposed theoretical measures produced an unexpected result: of the DSSs compared, the δ-type analytic hierarchy process (AHP) with consistency is the least efficient DSS, while the ε-type AHP with consistency is the most efficient DSS. This result has important implications for the design of DSSs.

The rest of the paper is organized as follows: Section 2 presents a brief review of the relevant literature. Section 3 shows the construction of the proposed model, introducing its structure and the main notation. The judgments and rationality of the experts are discussed in Section 4. Section 5 provides examples of the coding of the components of a DSS. Section 6 analyzes and discusses the results using a theoretical case study. The main conclusions are presented in Section 7.

2. Literature review

A recurring question in decision science is the following: "What is the most appropriate DSS for a given decision problem" [14]? A DSS is a formal scientific method aimed at framing a decision problem with structured and traceable algorithms of the information needed to comprehensively evaluate the decision alternatives to establish a priority vector, i.e., a best-to-worst ranking of the alternatives [15].

The proposed approach in this paper is based on the "bounded rationality" conceptual framework proposed by Simon [7,16,17] that hypothesizes the existence of a single optimal alternative and that differences in alternative judgments between systems or between experts arise from their inability to manage all available information. This hypothesis implies that a system or expert that manages all information (perfect information) will be able to select the best alternative without error. This perspective focuses on improving information management to find the best alternative, making the system or expert responsible for collecting data to improve performance.

DSSs for structured decisions [7] are systems in which decisions are repetitive, allowing the construction of a structure of relevant data. These DSSs fit well into Simon's conceptual framework because their goal is to improve the quantifiable performance, where the repetition of decisions allows them to learn about relevant information. In this domain, DSSs facilitate the analysis and presentation of objective data systematically collected through previous experience, thus significantly increasing the level of information available to decision-makers. The algorithmization of decision processes is essential to managing large amounts of data, especially in environments characterized by big data [18]. In business or organizational contexts, information systems help identify optimal solutions and improve competitiveness by integrating data across systems [19]. This has yielded fruitful results in a wide variety of areas, such as optimizing production scheduling [20], assessing sustainability across multiple supply chains [21], improving innovation outcomes using artificial intelligence [22], optimizing medical decisions [23], optimizing an organization's operations [24], optimizing transportation infrastructure [25], and making predictions [26].

However, unstructured decisions lack systematized prior information because they aim to respond to dynamic problems pervaded by uncertainty, making the formalization of the relationships between variables difficult [7] and expert judgments a crucial source of information [27–30]. Nevertheless, DSSs based on judgment of experts are extremely difficult to model and evaluate mainly due to, among other factors, the lack of reliability of judgments [31], the manifestation of contradictions within the judgments of individual experts [32], and the contradictions between the judgments of different experts [33]. In addition, in unstructured decisions, the performance of alternatives may be difficult to determine a priori and, sometimes, even a posteriori (after the decision has been made) when it is only possible to quantify the performance of the course of action [34].

The most widely used conceptual framework in DSSs based on judgments proposes a non-deterministic (utility or other) or unknown performance of the alternatives [35], which makes it impossible to distinguish between judgment errors or differences in preferences. The lack of a clear objective requires a DSS to be flexible to adapt to the circumstances of the problem [36], generating difficulties in aggregating and comparing judgments, and the contribution of the DSS must be established through indirect measures such as the level of agreement, consistency, or resilience of the result.

Within this traditional conceptual framework, researchers have developed general or global DSS models based on judgment of experts that do not distinguish between the information level, quality constraints, and performance. Thus, quality measures such as the level of consensus and level of consistency of experts, among others, are sometimes considered performance indicators for DSSs [37–39]. It is a challenge to improve a "hard-to-quantify performance," and the development of DSSs based on judgment of experts in the specialized literature has been carried out by increasing their sophistication and complexity for different aspects of the decision problem:

a) The number of judgments required: Holistic judgment requires only a ranking of the alternatives [40] versus performing pairwise judgments of the alternatives [41].
b) The type of judgment information required: A preference judgment only shows which of the alternatives is preferred [42]; an intensity judgment quantifies how much one alternative is preferred over another [43]; and a fuzzy intensity judgment also includes a degree of expert hesitation [44].
c) The type of consistency requirement: Ordinal consistency (if a is preferred to b and b is preferred to c, then c is preferred to a) [45]

versus cardinal consistency (if a is preferred to b 3 times and b is preferred to c 2 times, then c is preferred to a 6 times) [46] must be considered.

d) The type of consensus required: Ordinal consensus (measures the distance between the rankings of alternatives of different experts) [47,48] versus cardinal consensus (measures the distance between the intensities of preference shown by different experts) [49,50] must be considered.

Solving algorithm complexity: The AHP introduces intensity into pairwise judgments; the fuzzy AHP (FAHP) introduces fuzzy sets into the AHP to resolve uncertainties about expert preferences [51]; and the intuitionistic fuzzy AHP (IFAHP) allows a higher accuracy than the FAHP by simultaneously expressing affirmation, negation, and hesitation [44] but requires defuzzification to convert intuitionistic outputs into crisp numbers [52].

The traditional conceptual framework has led to the development of a wide variety of DSSs based on judgments, which are extraordinarily complex, either preventing comparisons between different DSSs or preventing quantifying their contributions to performance, making it impossible to quantify their efficiency. This paper leverages the developed intentional bounded rationality methodology [28] in Simon's bounded rationality framework for DSSs based on judgments. This approach uses the regularity existing in the errors of expert judgments regarding the performance of alternatives [53] to quantify any DSS or any of its parts by establishing a probability distribution that depends on the performance of the decision alternatives.

Within this conceptual framework, studies have been published in different decision domains, such as the demand for service platforms [54], how to quantify human error in Stackelberg games [55], forest fire management [56], the analysis of the impact of influence communication networks on group performance [57], the influence of participation in innovation decisions [58,59], the analysis of the theoretical advantages of blockchain technology [5], and how to balance experience, diversity, and the number of members in steering committees [29].

This paper's main objective is to propose a general codification of a DSS based on judgments that makes it possible to quantify not only the final priority vector but also the expected performance contributions of each of the parts that compose the DSS; this, recognizing that increasing the judgments means increasing the time spent by the experts (costs), will make it possible to perform an efficiency analysis of these DSSs with respect to their costs.

It has been suggested in the existing literature that increasing the number of judgments is costly, and it was questioned whether the increase in accuracy compensates for such an increase in cost [42]. Reducing the number of judgments in some DSSs may affect the accuracy of decisions in complex scenarios. To minimize this effect, sequential models [60], consistency measures [61], multigranularity models [62], and heuristics were proposed [63]. Other existing research works have tried to find DSSs based on algorithms that improve the accuracy of complex decisions by reducing errors through adaptive algorithms [64] or by combining judgments and databases [65]. In fact, whether the effort involved in implementing a DSS is worthwhile for unstructured decisions has been questioned by some researchers, with some findings revealing that more than 70 % of DSSs are not used systematically in the medical field [66]. This highlights the need to be able to evaluate the effectiveness of DSSs based on judgment of experts.

3. Model construction

This study proposes a model to evaluate the efficiency of DSSs, especially those based on judgment of experts. Technological developments have significantly reduced computational costs, but expert time is still valuable. In the literature, complex DSSs have been developed with the aim of enhancing the precision of their decision methodology. Although these DSSs impose a high time burden on experts, they do not consider whether the time cost compensates for the gain in precision. We define the efficiency of a DSS as the contribution of the DSS over a random (uninformed) decision per unit of judgment. The modeling of the efficiency of a DSS, the main notation, and the steps of the modeling framework are described below.

Let $A = \{A_1, ..., A_n\}$ be a finite set of $n = |A|$ alternatives with set latent performance values $V = \{V_1, ..., V_n\}$. Alternatives with the same latent performance values can be assumed to be equal and therefore only one is kept. Thus, without loss of generality, it is assumed that all latent performance values are different.

We use the phrase *combination of judgments* to mean the information requirement of a DSS based on judgment of experts. Thus, with DSS_y denoting a particular DSS (AHP, ordering, SMARTER, etc.), its information requirement on the set of alternatives is herein denoted by $G(DSS_y)$. The priority vector of alternatives for DSS_y is derived by applying its specific algorithm to $G(DSS_y)$. The sample space, denoted by $\gamma(DSS_y) = \{G^1(DSS_y), \ldots, G^M(DSS_y)\}$, is the set of all possible *combinations of judgments*, and its cardinality, $M = |\gamma(DSS_y)|$, depends on n.

Each DSS specifies the judgment values on the alternatives that can be used by the experts (more on this in Section 4). Thus, denoting by $R = \{R_1, \ldots, R_K\}$ the specific set of judgment values on the set of alternatives of DSS_y and denoting by $g_i^x \in R$ the value chosen by expert x for judging alternative A_i, $G^x(DSS_y) = \{g_1^x, g_2^x, \ldots, g_n^x\}$ represents one *combination of judgments* on the set of alternatives that expert x can choose from the sample space $\gamma(DSS_y)$ when analyzing the decision problem with DSS_y (some examples are given in Appendix II).

The goal of the proposed model is to determine the efficiency of the DSS based on three explanatory variables: the number of alternatives (n), their performance (V), and the precision of the expert (β^x), which, for simplicity, is assumed to be the same for all experts ($\beta^x = \beta$).

3.1. DSS performance

As mentioned before, once the *combination of judgments* is obtained from expert x ($G^x(DSS_y)$), a specific algorithm to DSS_y, and a priority vector of alternatives, $S^x(DSS_y) = (A_{k_1} \succ A_{k_2} \succ \cdots \succ A_{k_n})$, is derived as the solution of the decision problem. Notice that it is not possible to evaluate the quality of the derived solution $S^x(DSS_y)$ when the set of alternative performance values V is unknown and the *combination of judgments* $G^x(DSS_y)$ is the only available information on the set of alternatives. In this case, the intentional bounded rationality methodology (IBRM) is postulated as a methodological approach to evaluate the expected performance of a DSS based on judgment of experts. In the IBRM, the judgment value $g_i \in R$ chosen in judging alternative A_i is assigned a probability value based on the relative performance of the alternative and the precision of the expert: $p_{g_i} = \phi(V_i, \beta)$. The IBRM approach processes all the possible *combinations of judgments* on the set of alternatives to compute the expected performance of DSSs as a function of the exogenous variables V (performances of the alternatives), β (precision of the expert), and n (number of alternatives):

$$E[DSS_y] = \psi(V, \beta, n).$$

This is done with the three-step process below:

1) Set up a hypothetical scenario where the performance of the alternatives V is assumed to be known to allow the computation of each *combination of judgments* $G^k(DSS_y)$, a priority vector, $S^k(DSS_y)$, and its performance value, S^k. If the problem aim is to choose only one alternative from $S^k(DSS_y)$, then the performance of this priority vector will be $S^k = V_{k_1}$.
2) Obtain the sample space $\gamma(DSS_y) = \{G^1(DSS_y), \ldots, G^M(DSS_y)\}$ and assign each *combination of judgments* the probability value $p_{G^k(DSS_y)} = \prod_i^n p_{g_i^k}$.

3) The expected performance of the DSS for V: $E[DSS_y] = \sum_{k=1}^{M} p_{G^k(DSS_y)} S^k$.

3.2. DSS cost

The expected performance provides a benchmark against which to compare different decision strategies [67]. The expected performance of making a random decision was defined herein as the "profit of ignorance" expectation. A decision strategy is to be considered when its expected performance is higher than the corresponding profit of ignorance expectation. Thus, different courses of action can be evaluated and compared even before they are implemented by calculating the respective differences between their expected performance value and the profit of ignorance expectation, making this a useful metric in decision theory. The profit of ignorance represents the opportunity cost of not using any resources in the decision process and, since it is common for professionals to charge for a project based on its volume or expected initial value, it can be considered the reference point for measuring the cost of a DSS. Thus, a DSS is worth considering if it provides a performance that exceeds the profit of ignorance expectation.

No matter the decision problem, the selection of a random alternative as the solution to the problem costs nothing. The performance of the profit of ignorance is $E(PI) = \frac{1}{n}\sum_{i=1}^{n} V_i$. The *maximum admissible cost*, *MA*, of DSS_y is defined here as its contribution above the profit of ignorance, i.e.,

$$MA(DSS_y) = E[DSS_y] - E(PI). \tag{1}$$

It is obvious that *MA* depends on the exogenous variables (V, β, n) :

$$MA(DSS_y) = \varphi(V, \beta, n).$$

The most valuable resource in any DSS is the expert's judgment. If the cost per judgment is denoted by $h(>0)$, then the cost of a *combination of judgments* $G(DSS_y)$ in DSS_y will be $h|G(DSS_y)|$. However, quality requirements (QR) to be considered in implementing DSS_y may imply the unacceptability of some *combination of judgments*. Thus, if an expert provides an unacceptable *combination of judgments*, this is rejected, and the expert is asked to provide another acceptable *combination of judgments*. Let $QR(DSS_y)$ be the subset of the *combination of judgments* in $\gamma(DSS_y)$ containing unacceptable judgments. The probability of rejection of a *combination of judgments* in implementing DSS_y, denoted by $p(QR(DSS_y))$, is obtained as the sum of the probabilities of the *combination of judgments* in $QR(DSS_y)$. Thus, the cost of implementing DSS_y is

$$h|G(DSS_y)| + hp(QR(DSS_y))|G(DSS_y)| \\ = h(1 + p(QR(DSS_y)))|G(DSS_y)|.$$

As per the above, DSS_y is worth implementing only when its *MA* value is equal to or greater than its implementation cost:

$$MA(DSS_y) \geq h(1 + p(QR(DSS_y)))|G(DSS_y)|. \tag{2}$$

3.3. DSS efficiency

The goal of a DSS is to propose the priority vector that maximizes performance. The maximum performance is denoted as *MV* and its value depends on the scenario (*V*) and the type of problem faced (i.e., the number of alternatives of the priority vector that form the solution to the problem).

Notice that from Eq. (2), we obtain the upper cost per expert's judgment for DSS_y to be worth implementing:

$$h \leq \frac{E[DSS_y] - E(PI)}{(1 + p(QR(DSS_y)))|G(DSS_y)|}.$$

The efficiency of DSS_y is defined as the "*break-even point*" ($BEP_y(h)$), which is the ratio of the maximum cost per expert's judgment that can be paid for its implementation to its maximum performance:

$$BEP_y(h) = \frac{E[DSS_y] - E(PI)}{(1 + p(QR(DSS_y)))|G(DSS_y)|MV}.$$

This definition of the break-even point as a ratio eliminates scaling problems when comparing the efficiency of the implementation of different DSSs. It is noticed that efficiency also depends on the exogenous variables (V, β, n):

$$BEP_y(h) = \Omega(V, \beta, n). \tag{3}$$

Therefore, DSS_y is worth implementing if the cost per expert's judgment (h) is less than the break-even point ($BEP_y(h)$) multiplied by the maximum performance (*MV*). The greater the break-even point of a DSS, the greater the cost per expert's judgment the DSS can handle and, therefore, the greater the DSS's efficiency.

Traditionally, DSSs have been evaluated by performing sensitivity or consensus-level analyses on a specific case study (see Fig. 1) with known expert judgments (provided or constructed) from which "a posteriori analyses" of the DSSs' performances can be carried out. In this paper, however, the model proposed allows one to obtain the efficiency (*BEP*) of DSSs using the required exogenous variable values (V, β, n), considering all the possible judgments that can be provided by experts; this allows an "a priori evaluation" of the most appropriate DSS for each problem (see Fig. 2).

The evaluation model proposed in this paper is systematic because it generalizes the way DSSs are coded, and it is quantitative because it provides a comparable value for the efficiency of DSSs. The proposed method is summarized in Eqs. (1)-(3) and is based on: i) a solid conceptual framework based on intentional bounded rationality (IBR) [28, 68]; ii) previous empirical evidence on probabilistic regularity in expert judgments [69–74]; iii) theories that claim the economic value of ignorance as a reference in decision-making [75,76]; iv) the theory of the economic value of additional information, which relates the expected performance of a DSS to the gain from ignorance [77–81]; v) the results are consistent with previous research on DSS that implicitly used the proposed method [5,29,33,57,58,82,83]; vi) Section 6 presents a detailed case study demonstrating the applicability of the model to both δ and ε problems, showing reproducible and quantifiable results.

This is of interest to (1) managers and directors because it provides information on the possible gain percentages of a DSS compared to not using it and (2) researchers because it allows them to compare the efficiency of different DSSs in the same scenario and to justify increasing (or not increasing) their complexity.

4. Judgments and intentional bounded rationality

People can quickly identify similarities and differences between objects, concepts, or alternatives. Cognitive psychology studies have shown that humans have a great ability to recognize patterns and make comparative judgments in fractions of a second, demonstrating that the human mind is unique in integrating information and extracting abstract relationships [84], which is especially important when it is faced with unstructured decisions in rapidly changing environments.

Human judgment is a very fast synthesis tool, but it is difficult to use it scientifically if we are not able to model it [85]. In the absence of structured information, comparisons between alternatives help in categorization and decision-making. From neuroscience to cognitive psychology, there is ample evidence that the human brain has a great ability to make quick and effective comparisons between alternatives and can therefore be a valuable tool for science. Indeed, humans compare alternatives and evaluate their differences to classify them into categories to make more effective judgments [86]. The human brain uses comparisons all the time in language and thought. The ubiquitous use of metaphors, analogies, and comparative judgments in natural language

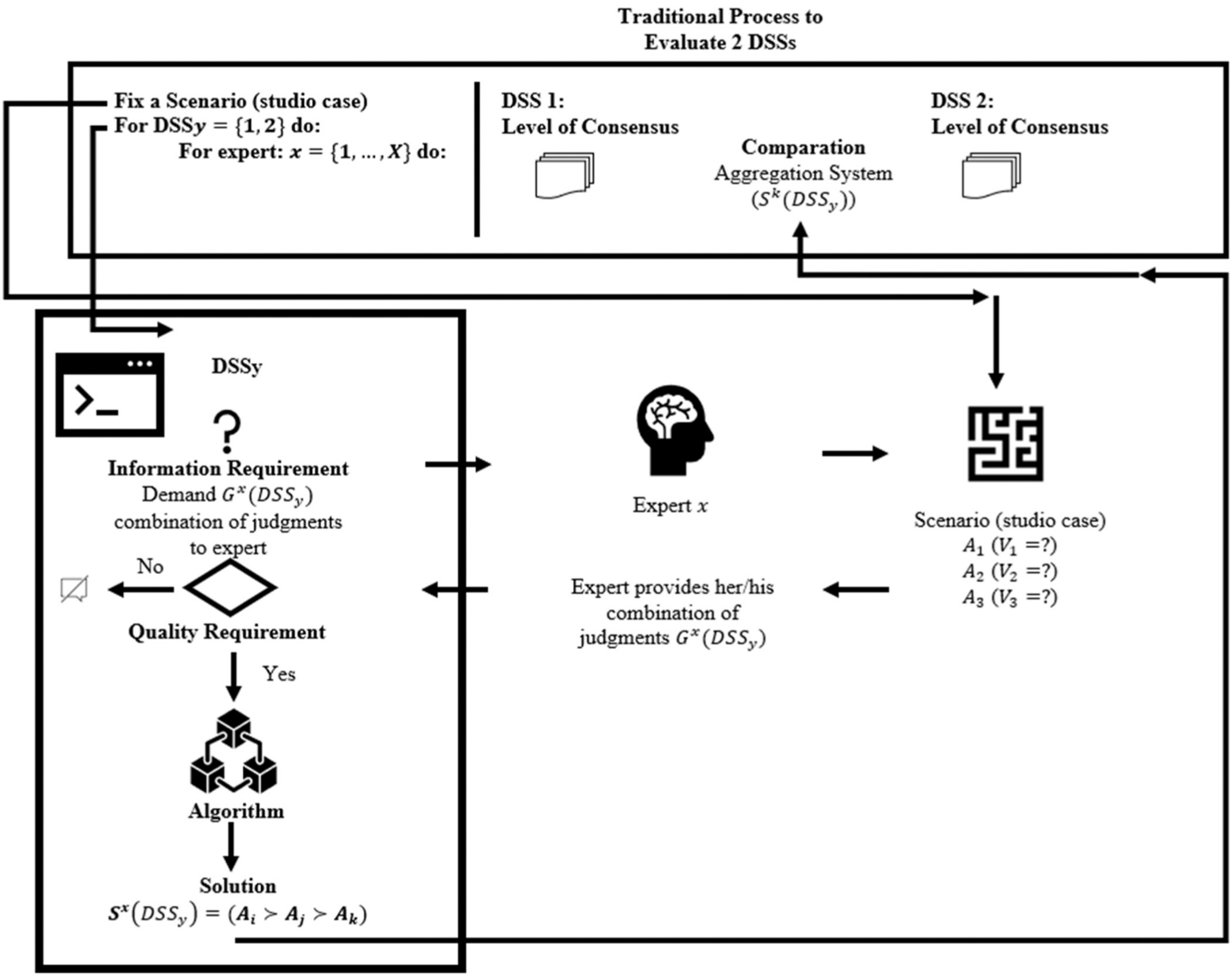

Fig. 1. Traditional process for evaluating DSSs.

suggests the importance of this human cognitive ability [87].

Many experiments have shown that judgments, even those of experts, exhibit errors that violate the axioms of rationality [88,89]. Advances in science have provided insight into how the human mind works. The brain is bombarded by millions of sensory impulses, but consciousness can only process a low number of aspects at a time (seven plus or minus two) [90]. The impulses must be condensed, ordered, and interpreted under immense time pressure, making it impossible to avoid errors and distortions [91]. Simon [16] coined the term bounded rationality to describe the natural inability of human beings to process all available information, despite their constant intention to be rational. This means that experts make judgments in which they do the best information processing they can within their cognitive and time constraints. The modeling of expert judgments cannot be the result of noisy information signals that follow a purely random distribution [92–94] but must be a reasonable consequence of the temporal and cognitive limitations of the experts, depending on the degree of the level of complexity of the choice.

The IBR proposes a theoretical framework in which the information available in reality is complete and human limitations do not allow it to be managed in its entirety [53]. The more precise the analysis or judgment must be, the higher the level of information that must be processed. The IBR proposes a relationship between the error and the difference in performance between alternatives, which are key in different methodological approaches such as the decision-maker's screening functions [95–97], the discrete choice theory [73,74], the full-rank log-odds model [69–72], and the evolutionary algorithm theories [98–100]. In fact, the IBR complements all these approaches by allowing the existence of prior beliefs and linking the quality of the outcome to the expertise of the person making the judgment.

The regularity of the IBR judgments (g_i) is summarized in a probability function for each alternative as if it were a physical law of particles. Each expert expresses his/her judgment in favor of one of the alternatives, with a certain degree of error. The expert's ability to make a correct judgment (g_i) depends on his/her level of expertise (precision) when it comes to processing information or signals (β) related to the latent performance values (V_i) of the alternatives. In other words, this approach allows one to establish the probability of the expert's judgments on the alternatives based on V and the expert's precision β : $p_{g_i} = \phi(V, \beta)$.

On the one hand, it is reasonable to assume that the probability of making a choice error can be accurately captured by the differences between the performance values of the alternatives, so tradeoffs between alternatives are expressed in terms of such differences. Since it is also important to avoid scaling effects, the performance values of alternatives are normalized prior to their computational processing: $v_i = \frac{V_i}{\sum_{k=1}^{n} V_k}$. On the other hand, the importance of the parameter β resides in its modeling of the expert's ability to process information. If the expert does not know anything about a problem, does not have the ability to

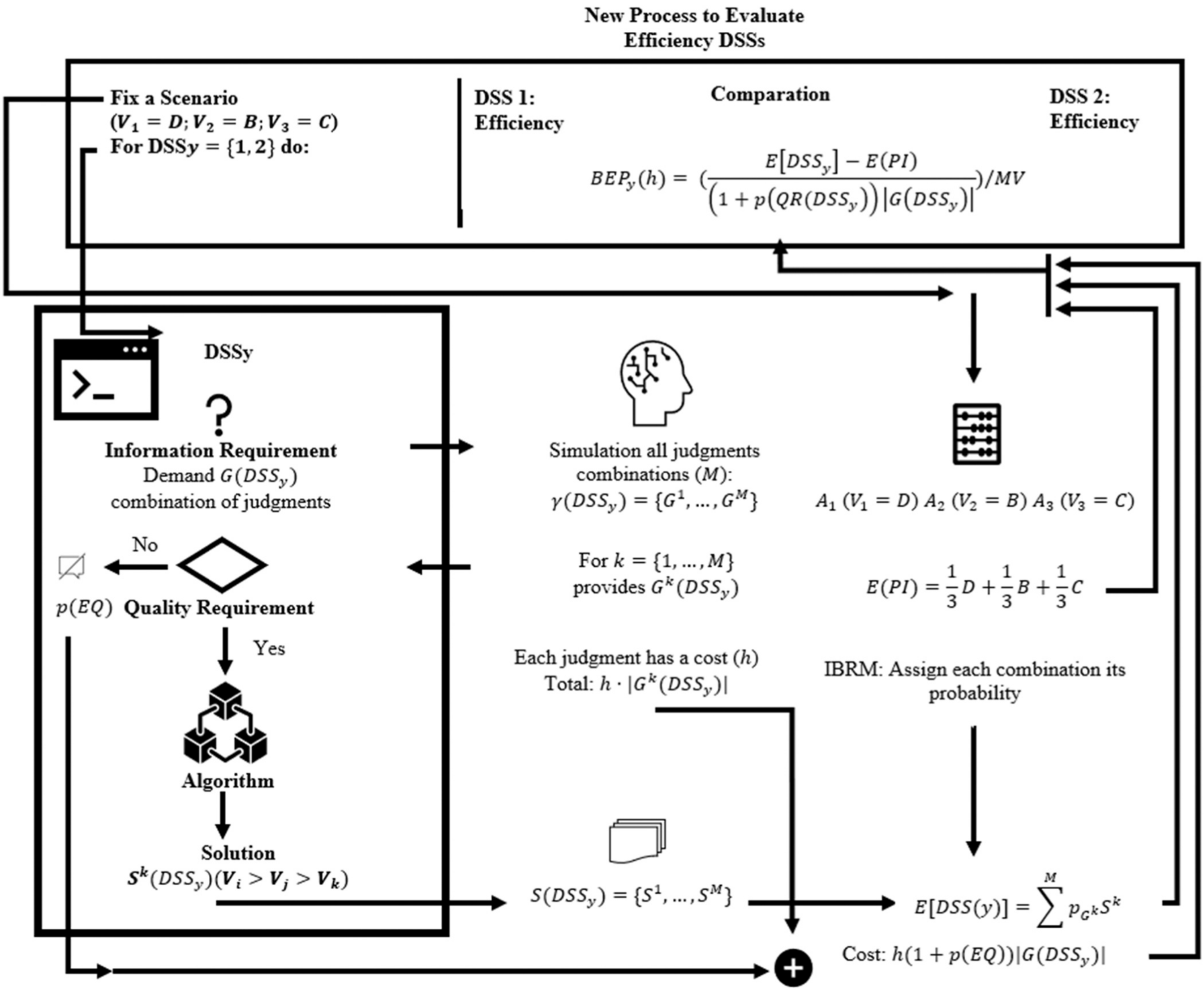

Fig. 2. New process for evaluating DSSs.

process information, or does not know what the relevant information is, then $\beta = 0$, and all alternatives will have the same probability of being chosen as the best regardless of their latent performances. High values of β imply a high capacity to process information, and the higher the value of β, the higher the probability of choosing as the best alternative the one with the highest latent performance value.

For example, the probability of alternative A_i being chosen as the best alternative ($p_{g_{iA}}$) by an expert with a level of precision β based on a holistic judgment of preference comparison (g_{iA}) is expressed by the following formula:

$$p_{g_{iA}} = \frac{e^{\beta v_i}}{\sum_{j=1}^{n} e^{\beta v_j}} = \frac{1}{1 + \sum_{j \neq i}^{n} e^{\beta (v_j - v_i)}}. \tag{4}$$

The probability of choosing an alternative other than A_i is $\sum_{j \neq i}^{n} p_{g_{jA}} = 1 - p_{g_{iA}}$. Although any alternative has a probability of being chosen by an expert, those alternatives that perform the worst are less likely to be selected as the best alternative.

5. Coding the DSSs

The analysis of a DSS based on judgment of experts is proposed to be carried out in three structural parts: 1) information requirements—the systematic information required; 2) quality requirements—the mechanisms used to ensure quality; 3) algorithms—the processing of the information using algorithms to provide a solution proposal (priority vector).

5.1. Information requirements

Expert judgments are particularly valuable for those elements of the problem that are difficult to quantify. For example, the evaluation of the comfort or drivability of a car cannot be quantified with tools rather than expert opinions or judgments. Each DSS determines which judgments the expert can make, how many judgments are required for a given set of alternatives, and the information content conveyed by each of the judgments. For example, assume that we are interested in the comfort of three cars (A, B, C) and DSS_1 requires pairwise comparison judgments (A vs. B; A vs. C; B vs. C), with the information content of judgments being "very preferred to" (2.5), "preferred to" (1.5), "less preferred to" (1/1.5), and "much less preferred to" (1/2.5). Thus, in DSS_1 a *combination of judgments* is denoted $G(DSS_1) = \{g_{AB}, g_{AC}, g_{BC}\}$ and each of its three judgments ($|G(DSS_1)| = 3$) can take one of four values in $R = \{1/2.5; 1/1.5; 1.5; 2.5\}$. A possible *combination of judgments* would be $G^1(DSS_1) = \{g^1_{AB} = 1.5, g^1_{AC} = 2.5, g^1_{BC} = 1.5\}$. A generalized coding of this part is not easy due to the diversity of DSS approaches, i.e., the diverse nature of R, the semantics associated with each element of R, and the evaluation of alternatives with elements of R. Despite this, some illustrative examples of the procedure to obtain the necessary information in our model are presented below. To simplify the problem, it will be assumed that all the judgments made by an expert require a unit of time for reflection and contribution.

The two main basic paradigms used to evaluate alternatives are holistic evaluation and pairwise comparison evaluation [101]. As already mentioned, the pairwise comparison evaluation of alternatives requires a greater number of judgments $n(n-1)/2$ than the holistic evaluation of alternatives, where an expert is asked to rank the available alternatives from highest to lowest and, therefore, only n judgments are required.

In the presence of a set of criteria $D = \{D_1, D_2, \ldots, D_d\}$, the following decomposition approach is required. If $B = \{b_{ij}\}$ is the normalized performance matrix representing the scores of the alternative A_i with respect to the criterion D_j $\left(g_{ij} = b_{ij}\right)$ and $w = \{w_1, w_2, \ldots, w_d\}$ is the importance (weight) vector of the criteria set $D(g_i = w_i)$, then the overall score of each alternative A_i is derived by applying an aggregation operation, which could be the weighted average: $v_i = \sum_{j=1}^{d} w_j b_{ij}$. In this case, an expert must provide a set of weights and the normalized score of each alternative A_i with respect to each of the criteria D_j over the alternative A_i. Thus, a *combination of judgments* in the holistic decomposition evaluation requires $d + d{\cdot}n(= |G(DSS_{hol})|)$ judgments, while a *combination of judgments* in the pairwise evaluation requires $\frac{d(d-1)}{2} + d{\cdot}\frac{n(n-1)}{2}$ $\left(= \left|G\left(DSS_{pai}\right)\right|\right)$ judgments.

The "Borda" system is a well-known holistic DSS. Named after the application proposed by Jean-Charles de Borda in 1770 [102], it is a positional scoring rule that assigns a score to each of the n alternatives. The most preferred alternative gets the maximum score of n, the second-most preferred gets a score of $n-1$, and so on. The system was designed for voting processes on candidates and its goal was to allow each expert to express a complete ranking of alternatives rather than just indicating the best alternative. There is an isomorphism between the performance values of alternatives and the set of score values $R = \{n, n-1, \ldots, 2, 1\}$ in the Borda system. In this system, an expert's *combination of judgments* requires $n(= |G(DSS_{Bor})|)$ judgments.

The Ordering system, when applied without decomposition, is a simple pairwise comparison system with a *combination of judgments* of cardinality $|G(DSS_{Ord})| = n(n-1)/2$ [42]. The expert compares two alternatives (A_i, A_j) at a time and must express a judgment to reflect whether the first alternative is the preferred alternative $(g_{ij} = 1)$ or not, i.e., the second alternative is the preferred alternative $(g_{ij} = 0)$. Thus, $R = \{0, 1\}$. The reciprocity property, $g_{ji} = 1 - g_{ij}$, is usually imposed. In this case, the relationship of judgments with performance values becomes $g_{ij} = 1$ if V_i is greater than V_j. The priority vector of alternatives is obtained by applying a scoring function (algorithm), such as $r_i = \sum_{j=1, i \neq j}^{n} g_{ij}$, that assigns to the alternative A_i the number of alternatives not preferred to (with a lower performance value than) A_i, followed by the ranking of score values from highest to lowest.

The simple multi-attribute rating technique exploiting ranks (SMARTER) is a holistic decomposition system with a *combination of judgments* of cardinality $|G(DSS_{SMA})| = d + d{\cdot}n$ [40]. It is a DSS designed according to the principles of multi-attribute utility theory [103], with standardized performances b_{ij} representing the contribution of the attribute D_j to the performance of the alternative A_i; the algorithm for calculating the normalized performance of alternative A_i is $v_i = \sum_{j=1}^{m} w_j b_{ij}$, and ranking the results from highest to lowest produces the priority vector of alternatives.

The AHP is a pairwise decomposition system [104] (although it can be used without decomposition). The expert is required to make pairwise judgments of relative comparisons of the importance of the d criteria (D_j), quantifying them cardinally, i.e., $z_{ij} = \frac{D_i}{D_j}$ is the pairwise comparison of the importance of criteria D_i with respect to the importance of criteria D_j. The solution algorithm constructs a reciprocal matrix of the expert's pairwise judgments $Z = (z_{ij})_{dxd}$, with the normalized solution vector w^z $\left(\sum_j^d w_j^z = 1\right)$ of the equation $(Z - dI)w^z = 0$ being the weight of each criterion. Then, the expert is asked to compare alternatives in pairs, based on their performances $\left(V_{i,k}, V_{j,k}\right)$ with respect to each criterion D_k, and provide pairwise comparison judgments $a_{ij,k} = \frac{V_{i,k}}{V_{j,k}}$. The described solution algorithm applied to the expert's reciprocal matrix of pairwise judgments for criterion D_k, $L_k = \left(a_{ij,k}\right)_{nxn}$, gives a normalized priority vector of alternatives for criterion D_k: $w^{a,k}$ $\left(\sum_i^n w_i^{a,k} = 1\right)$. The algorithm for the final evaluation of the alternative A_i is the weighted average: $w_i = \sum_{j=1}^{d} w_j^z {\cdot} w_i^{a,j}$. The final priority vector $w = \{w_1, w_2, \ldots, w_n\}$, ranked from highest to lowest, results in the priority vector of alternatives, or the alternative proposed as a solution is the one with the highest priority value, $\max_i w_i$. An expert's *combination of judgments* $G(DSS_{AHP}) = \left\{g_{12}(z), \ldots, g_{(d-1)d}(z), g_{12,k}(a), \ldots, g_{nd,k}(a)\right\}$ has cardinality $|G(DSS_{AHP})| = \frac{d(d-1)}{2} + d{\cdot}\frac{n(n-1)}{2}$.

Once the *combination of judgments* of the DSS is identified, the sample space of the *combinations of judgments* is obtained: $\gamma\left(DSS_y\right) = \left\{G^1\left(DSS_y\right), \ldots, G^M\left(DSS_y\right)\right\}$. For a decision problem, the following conjecture is plausible: the higher the cardinality of the *combination of judgments* of a DSS, the more informative the DSS is for the decision problem, and the higher its efficiency. Regardless, even in the case in which this conjecture is true, the question worth answering is whether the gain in efficiency obtained by increasing the information compensates for the costs of such an increase in information.

5.2. Quality requirements

DSSs based on judgments handle "subjective" information, and it is common for them to establish judgment selection mechanisms (quality requirements) to guarantee the quality of the solution. Quality requirements can be implemented prior to the DSS or can be integrated into it. When they are prior, they are established as a cost outside the system. The most common is based on the prestige or reputation of the expert, which impacts the price of the judgments. DSSs that incorporate quality constraints are based on the logical relationships of the judgments provided by the expert. One of the most common is the requirement of the consistency of judgments. It is possible to implement a consistency quality constraint in a pairwise comparison paradigm DSS but not in a holistic paradigm DSS.

The Ordering information requirement would reject judgments that violate the following transitivity of comparisons (ordinal consistency): if A_i is preferred to A_j $(A_i \succ A_j)$ and A_j is preferred to A_k $(A_k \succ A_k)$, then A_i is preferred to A_k $(A_i \succ A_k)$. Ordinal inconsistency has been proposed to be measured as a function of the ratio between the number of intransitive or circular triads (c) and the total number of triads: a circular triad is a set of three alternatives $\left(A_i, A_j, A_k\right)$ such that $A_i \succ A_j \succ A_k \succ A_i$. Kendall and Smith [45] proposed a coefficient that they called the consistency coefficient (Ke). Gass [105] proved that the number of circular triads in a pairwise comparison of alternatives is $c = \frac{n(n-1)(2n-1)}{12} - \frac{1}{2}\sum_{i=1}^{n}\left(\sum_{j=1}^{n} g_{ij}^x\right)^2$. In general, when Ke is above 0.75 $(QR = Ke > 0.75)$, [105] the *combination of judgments* provided by the expert $(G^x(DSS))$ is acceptable.

In the AHP, the information requirement would reject judgments that violate the following cardinal consistency: if A_i is preferred a_{ij} times to A_j, A_j is preferred a_{jk} times to A_k, and A_i is preferred a_{ik} times to A_k, then $a_{ik} = a_{ij}{\cdot}a_{jk}$. Saaty presented in [104] a consistency ratio based on the largest eigenvalue of Z and a random index RI_n, $CR = \frac{\lambda_{\max} - n}{(n-1){\cdot}RI_n}$, which must be less than 0.1 $(QR = CR < 0.1)$ for the *combination of* *judgments* expressed by the expert ($G^x(DSS)$) to be acceptable.

It is possible to calculate *QR* from the sample space $\gamma(DSS)$, i.e., from all possible *combinations of judgments* required by a DSS $\{G^1(DSS), \ldots, G^M(DSS)\}$, we can classify *combinations of judgments* into two classes: acceptable and not acceptable. Since the IBRM allows the calculation of the probability of each possible *combination of judgments*, it is possible to calculate the probability that the DSS will reject a given quality requirement mechanism ($p(QR(DSS))$ by adding the probabilities of the unacceptable combinations of judgments.

When the requirement for consistency is cardinal (AHP), this is more demanding than ordinal consistency (Ordering) because it is more likely a non-consistency to appear. Pairwise comparison requires more judgments than holistic comparison and can also eliminate judgments if they do not meet the consistency requirements, something that holistic evaluation does not allow. Therefore, the pairwise paradigm is much more informative than the holistic system.

There is research that has quantified the contribution to the expected performance of the AHP consistency requirement [28], but not its cost. Research that has measured the consistency requirement contribution in the AHP versus its contribution in the Ordering intuitively challenges this statement [42].

5.3. Algorithms

Given a *combination of judgments* $G^k(DSS_y)$, the algorithm of DSS_y derives a priority vector of the alternatives $S^k(DSS_y) = (A_{k_1} \succ A_{k_2} \succ \cdots \succ A_{k_n})$, and using the IBRM approach the performance of DSS_y can be calculated as follows (see Section 3.1, *DSS Performance*):

$$E[DSS_y] = \sum_{k=1}^{m} p_{G^k(DSS_y)} S^k. \tag{5}$$

6. Case study

A decision scenario is set up to illustrate the modeling of the efficiency of two DSSs, the AHP and the Ordering DSSs, with two different quality requirements, with and without consistency, for two different problems: the δ-type and ε-type problems. The decision scenario is set up with the same parameter values used in [42]: $\beta = 1$, $V_1 = 62.5$, $V_2 = 25$, and $V_3 = 10$.

The consistency requirement will be explicitly stated by sub-indexing the corresponding DSS: AHP_{wC} and AHP_{woC} represent the AHP with and without the consistency requirement, respectively. It is fair to say that the AHP is more informative, more quality-demanding, and more resolution-complex than the Ordering.

Information requirements: Since the Ordering and the AHP are pairwise judgment approaches, both have the same *combination of judgments* cardinality: $n(n-1)/2$. The difference between them resides in the requirement of the intensity of preference in the judgments by the AHP.

Quality requirement: As mentioned in Section 4.2, the consistency property in the AHP is cardinal, and in the Ordering, it is ordinal. Therefore, the AHP is more demanding than the Ordering and $p(QR(AHP_{wC})) > p(QR(Ord_{wC}))$.

Algorithm: Although the algorithm complexity of the AHP is higher than the algorithm complexity in the Ordering, this difference is not significant with the current computing power and, therefore, the computational cost is assumed to be zero for both DSSs.

The below IBRM relative pairwise comparison of performances is used to compare the implementation of both the Ordering and the AHP as DSSs in the considered decision scenario:

$$p_{g_{ij}} = \frac{e^{\beta\frac{V_i}{V_j}}}{e^{\beta\frac{V_i}{V_j}} + e^{\beta\frac{V_j}{V_i}}} = \frac{1}{e^{\beta\left(\frac{V_j}{V_i} - \frac{V_i}{V_j}\right)} + 1}. \tag{6}$$

- In the δ-type problem, the entire priority vector is important because the goal is to eliminate the alternative with the worst performance. The solution performance is the sum of the performances of all the alternatives except the last one; when two alternatives are tied in a priority vector, one of them is eliminated at random. Thus,

  $S_{123} = S_{213} = V_1 + V_2$; $S_{132} = S_{312} = V_1 + V_3$;
  $S_{231} = S_{321} = V_2 + V_3$; $S_{1=2=3} = 2(V_1 + V_2 + V_3)/3$.

  The *combinations of judgments* that have the same last alternative are grouped and their probabilities are added. The expected performance of the *DSS* is

$$E_\delta(DSS) = \left(p_{S_{123}} + p_{S_{213}}\right)(V_1 + V_2) + \left(p_{S_{132}} + p_{S_{312}}\right)(V_1 + V_3) + \left(p_{S_{321}} + p_{S_{231}}\right)(V_2 + V_3) + \left(p_{S_{1=2=3}}\right)\frac{2(V_1 + V_2 + V_3)}{3}. \tag{7}$$

  The maximum performance in this decision scenario is $MV_\delta = 62.5 + 25 = 87.5$.

  The profit of ignorance, $E_\delta(PI)$, is the probability of eliminating each alternative:

  $$E_\delta(PI) = \frac{1}{3}(V_1 + V_2) + \frac{1}{3}(V_1 + V_3) + \frac{1}{3}(V_2 + V_3) = 65.$$

- In the ε-type problem, only the alternative with the highest performance is selected. Thus, the first position of the priority vector is important. Thus,

  $S_{123} = S_{132} = V_1$; $S_{213} = S_{231} = V_2$;
  $S_{321} = S_{312} = V_3$; $S_{1=2=3} = (V_1 + V_2 + V_3)/3$.

  Rankings with the same first alternative are grouped, and their probabilities are added according to $p_i = \sum_{j\neq i}^{n} \sum_{k\neq i\neq j}^{n} p_{S_{ijk}}$, with their entry being the performance of the alternative considered best. In the case of a tie, one is chosen at random:
  $p_1 = p_{S_{123}} + p_{S_{132}}$; $p_2 = p_{S_{213}} + p_{S_{231}}$; $p_3 = p_{S_{321}} + p_{S_{312}}$; $p_{S_{1=2=3}}$.
  The expected performance of the *DSS* is

  $$E_\varepsilon(DSS) = p_1 V_1 + p_2 V_2 + p_3 V_3 + p_{S_{1=2=3}} \frac{(V_1 + V_2 + V_3)}{3} \tag{8}$$

  The maximum performance in this decision scenario is $MV_\varepsilon = 62.5$.
  The profit of ignorance in the ε-type problem, $E_\varepsilon(PI)$, is

$$E_\varepsilon(PI) = \frac{1}{3}V_1 + \frac{1}{3}V_2 + \frac{1}{3}V_3 = 48.8333.$$

6.1. Ordering

The ********Ordering *combination of judgments*, $G(Ord)$, is conveniently represented with a square matrix of judgments of dimension n, $G(Ord) = \begin{pmatrix} g_{11} & \cdots & g_{1n} \\ \vdots & \ddots & \vdots \\ g_{n1} & \cdots & g_{nn} \end{pmatrix}$, where $g_{ij} \in R(Ord) = \{0, 1\}$ (0: no preference; 1: preference). The reciprocity of judgments $g_{ij} = 1 \Longleftrightarrow g_{ji} = 0$ implies $n(n-1)/2$ judgments are required to completely construct matrix $G(Ord)$; $|G(Ord)| = n(n-1)/2$.

In the decision scenario, the sample space of *combinations of judgments* consists of eight matrices of judgments:

$$G^1(Ord) = \begin{pmatrix} - & 1 & 1 \\ 0 & - & 1 \\ 0 & 0 & - \end{pmatrix}, G^2(Ord) = \begin{pmatrix} - & 1 & 1 \\ 0 & - & 0 \\ 0 & 1 & - \end{pmatrix}, G^3(Ord) = \begin{pmatrix} - & 0 & 1 \\ 1 & - & 1 \\ 0 & 0 & - \end{pmatrix},$$

$$G^4(Ord) = \begin{pmatrix} - & 0 & 0 \\ 1 & - & 1 \\ 1 & 0 & - \end{pmatrix}, G^5(Ord) = \begin{pmatrix} - & 1 & 0 \\ 0 & - & 0 \\ 1 & 1 & - \end{pmatrix}, G^6(Ord) = \begin{pmatrix} - & 0 & 0 \\ 1 & - & 0 \\ 1 & 1 & - \end{pmatrix},$$

$$G^7(Ord) = \begin{pmatrix} - & 1 & 0 \\ 0 & - & 1 \\ 1 & 0 & - \end{pmatrix}, G^8(Ord) = \begin{pmatrix} - & 0 & 1 \\ 1 & - & 0 \\ 0 & 1 & - \end{pmatrix}.$$

Applying the Ordering algorithm $r_i = \sum_{j=1, i\neq j}^{n} g_{ij}$ to $G^1(Ord)$ results in $r_1 = 2$, $r_2 = 1$, $r_3 = 0$, and the priority vector of alternatives $r_1 > r_2 > r_3$, which is denoted by $S_{123}(G^1 Ord))$. Similarly, the eight priority vectors of alternatives obtained with Ord_{woC} are

$$S_{123}(G^1(Ord)); S_{132}(G^2(Ord)); S_{213}(G^3(Ord));$$

$$S_{231}(G^4(Ord)); S_{312}(G^5(Ord)); S_{321}(G^6(Ord));$$

$$S_{1=2=3}(G^7(Ord)) = S_{1=2=3}(G^8(Ord)).$$

In $G^7(Ord)$ and $G^8(Ord)$, $r_1 = r_2 = r_3 = 1$, and a tie between the three alternatives occurs. Computation details for the calculations below are available in Appendix I.

6.1.1. δ-type problem

Ordering without consistency (Ord_{woC}). As per the IBRM, the probability of each *combination of judgments* is obtained: $p_{G^k(Ord_{woC})} = \prod_{i\neq j}^{n} p_{g_{ij}}$, where $p_{g_{ij}}$ is computed according to Eq. (6). For example, $p_{G^1(Ord_{woC})} = p_{S_{123}(Ord_{woC})} = p_{12}p_{23}p_{13}$. According to Eq. (7), the expected performance of Ord_{woC} is

$$E_\delta(Ord_{woC}) = 85.7216.$$

In this case, there are no quality requirements, so $p(QR(Ord_{wC}) = 0$.

Ordering with consistency (Ord_{wC}). The two *combinations of judgments* $G^7(Ord)$, $G^8(Ord)$) do not satisfy ordinal consistency and are rejected. Since only consistent *combinations of judgments* are considered, the expected performance of Ord_{wC} is computed according to Eq. (7) without the rejected *combinations of judgments'* contributions (i.e., last right-hand term) and with the normalized probabilities of the consistent *combination of judgments*: $p_{G^k(Ord_{wC})} = p_{G^k(Ord_{woC})} / \sum_{k=1}^{6} p_{G^k(Ord_{woC})}$. Thus,

$$E_\delta(Ord_{wC}) = 86.3002.$$

The probability of rejecting a *combination of judgments* with ordinal consistency is $p(QR(Ord_{wC}) = 1 - \sum_{k=1}^{6} p_{G^k(Ord_{woC})} = 0.0137$.

6.1.2. ε-type problem

Ordering without consistency (Ord_{woC}). According to Eq. (8), the expected performance of Ord_{woC} is

$$E_\varepsilon(Ord_{woC}) = 58.4322.$$

Ordering with consistency (Ord_{wC}). As above, after eliminating the inconsistent *combinations of judgments*, the expected performance of Ord_{wC}, based on Eq. (8) without its last right-hand term and the normalized probabilities of the consistent *combination of judgments*, is

$$E_\varepsilon(Ord_{wC}) = 58.7916.$$

The probability of rejecting a *combination of judgments* with ordinal consistency is $p(QR(Ord_{wC}) = 0.0137$.

6.2. AHP

To allow a comparison with the ordering DSS, we will analyze the AHP without decomposition (for details on the simplification and application of the IBRM, see [42]).

An AHP *combination of judgments*, $G(AHP)$, is also conveniently represented by a reciprocal square preference comparison matrix of dimension n, $G(AHP) = (g_{ij})$, where $g_{ij}\left(= \frac{1}{g_{ji}}\right)$ is the expert's judgment about the number of times the performance of the alternative A_i, V_i, is greater than the performance of the alternative A_j, V_j, with the simplification of only four intensity intervals being considered in this decision scenario, i.e., $R(AHP) = \left\{\frac{25}{4}, \frac{10}{4}, \frac{4}{10}, \frac{4}{25}\right\}$, with 25/4 indicating that A_i is "extremely preferred" to A_j; 10/4 indicating that A_i is "preferred" to A_j; 4/10 indicating that A_j is "preferred" to A_i; and 4/25 indicating that A_j is "extremely preferred" to A_i. Accordingly, $|G(AHP)| = n(n-1)/2$. From $G(AHP) = (g_{ij})_{n\times n}$, the priority vector $S(AHP) = s = (s_1, \ldots, s_n)$ is obtained; this verifies $g_{ij} = s_i/s_j$ and $\sum_i^n s_i = 1$. In the decision scenario, the sample space of *combinations of judgments* has cardinality $64 = |\gamma(AHP)|$. As per the IBRM, the combination of judgment probability values $p_{G^k(AHP)} = \prod_{i\neq j}^{n} p_{g_{ij}}$, their consistency ratio $CR(G^k(AHP))$, and priority vectors $S(G^k(AHP))$ are obtained.

6.2.1. δ-type problem

AHP without consistency (AHP_{woC}). The computations to obtain the ranking (s) from the judgment matrix $G(AHP)$ are more complex than with Ordering since they involve solving the equation $(G(AHP) - \lambda_{\max}I)s = 0$, although this is not an issue for modern computer power. The expected performance of AHP_{woC} according to Eq. (7) is

$$E_\delta(AHP_{woC}) = 85.9540.$$

AHP with consistency (AHP_{wC}). A comparison matrix $G^k(AHP)$ is considered acceptable if $CR\left(G^k(AHP)\right) < 0.1$ [104]. In this case study, nearly one out of five *combinations of judgments* are rejected: $p(QR(AHP_{wC})) = 0.1949$. The expected performance of AHP_{wC} is computed according to Eq. (7) without its last right-hand term and the normalized probabilities of the consistent *combination of judgments*:

$$E_\delta(AHP_{wC}) = 87.0605.$$

6.2.2. ε-type problem

AHP without consistency (AHP_{woC}). According to Eq. (8), the expected performance of AHP_{woC} is

$$E_\varepsilon(AHP_{woC}) = 58.7366.$$

AHP with consistency (AHP_{wC}). By removing non-consistent matrices $(CR(G^k(AHP)) > 0.1)$, the expected performance of AHP_{wC}, based on Eq. (8) without its last right-hand term and the normalized probabilities of the consistent *combination of judgments*, is

$$E_\varepsilon(AHP_{wC}) = 61.4225.$$

6.3. Discussion

The analysis of the efficiency contributions, in the two proposed δ and ε problems, of the different DSS parts is carried out with the following four indicators:

1) DSS expected performance: $E(DSS_y)$;

2) Percentage of expected performance over maximum performance: $E\%MV = \frac{E(DSS_y)}{MV}$;

3) Maximum admissible cost: $MA = E(DSS_y) - E(PI)$;

4) Break-even point: BEP_y.

The procedure established by the model to obtain the proposed indicators to evaluate the efficiency of the DSS is shown schematically in Fig. 3.

At this point in the analysis, it is worth recalling that the existing literature has identified increasing both the complexity and requirements of a DSS as drivers for improving the DSS's expected performance. Table 1 shows the values of the four indicators for the δ-type problem, while Table 2 shows the corresponding values for the ε-type problem.

Table 1
Indicators in δ-type problem.

DSS	*E(DSS)(1)*	*E%MV (2)*	*MA (5)*	*BEP (7)*
Ord_{woC}	85.7216	97.97 %	20.7216	7.89 %
Ord_{wC}	86.3002	98.63 %	21.3002	8.00 %
AHP_{woC}	85.9540	98.23 %	20.9540	7.98 %
AHP_{wC}	87.0605	99.50 %	22.0605	7.03 %

Table 2
Indicators in ε-type problem.

DSS	*E(DSS)(1)*	*E%MV (2)*	*MA (5)*	*BEP (7)*
Ord_{woC}	58.4322	93.49 %	9.5989	5.12 %
Ord_{wC}	58.7916	94.07 %	9.9583	5.24 %
AHP_{woC}	58.7366	93.98 %	9.9033	5.28 %
AHP_{wC}	61.4225	98.28 %	12.5892	5.62 %

In both problems, the same expected performance ranking of the DSSs is obtained: $AHP_{wC} \succ Ord_{wC} \succ AHP_{woC} \succ Ord_{woC}$. Thus, the case study suggests the following:

1. The requirement of consistency in a DSS increases its performance.
2. With the same consistency requirements, increasing the complexity of the DSS increases its performance.
3. An increase in complexity on its own is not sufficient to guarantee an increase in performance because Ord_{wC} outperforms AHP_{woC} in both problems.
4. Each DSS performs better on the δ-type problem than on the ε-type problem, which indicates that considering the complete ranking of alternatives has a positive effect on the performance of the DSS.

The above increases have a caveat: they can be categorized as modest. First, the $E\%MV$ results indicate that the performances of all DSSs are very close to the corresponding problem's maximum performance. The increase in performance is noticeable for the AHP only in the ε-type problem, where it is more than 4 percentage points; otherwise, the gain in performance is below 1 percentage point. The same conclusion is observed when the complexity is increased with the same consistency requirements. The increase in performance is only noticeable in the ε-type problem with consistency, where it is more than 4 percentage points; otherwise, the gain in performance is below 1 percentage point. Although each DSS performs better on the δ-type problem than on the ε-type problem, the gains in performance for AHP_{wC} on the δ-type problem with respect to the ε-type problem are less than a quarter of a percentage point and, therefore, insignificant when compared with the gains in performance of more than 4 percentage points by the other three DSSs. The DSS that contributes most above the profit of ignorance

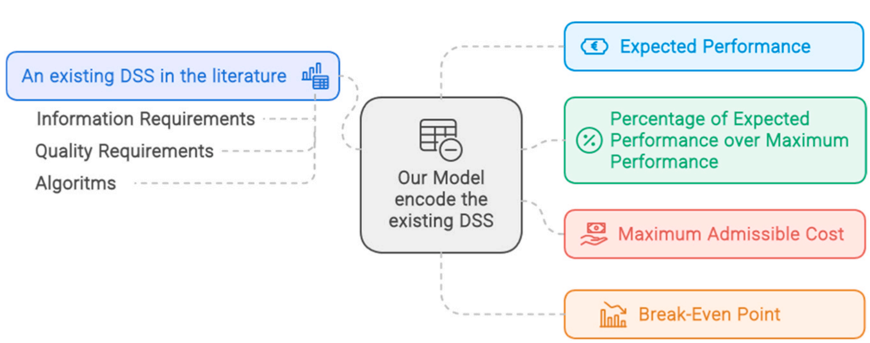

Fig. 3. Procedure for obtaining the indicators.

is AHP_{wC}. Thus, the joint contribution of an increase in complexity and the consistency requirement is positively reflected in the value of the maximum admissible costs in both problems.

Finally, recall that the greater the break-even point of a DSS, the greater the cost per expert's judgment the DSS can afford and, therefore, the greater the DSS's efficiency. These case study results suggest that the DSSs are more efficient for the δ-type problem. Although the differences in the efficiency values of the DSSs are small, especially within the same problem, it is interesting to notice that while AHP_{wC} is the most efficient for the ε-type problem, it is the least efficient for the δ-type problem, where Ord_{wC} is the most efficient.

The DSS evaluation method proposed in this paper has several unique advantages: i) it is a pioneering model to quantitatively evaluate the efficiency of DSSs a priori (before their implementation); ii) it provides specific metrics to quantify the expected costs and benefits of DSSs; iii) it allows systematic comparisons between different DSSs; iv) the results have practical implications for managers and researchers; v) it opens new lines of research by challenging the assumption that greater complexity implies greater efficiency.

7. Conclusions

Human judgment represents valuable information in decision-making, but the effort to accumulate knowledge and provide a judgment has a price (cost), and it must be used to ensure that the effort involved in achieving a decision is worthwhile. The literature has attempted to minimize the impact of human error in DSSs by developing complex systems that significantly increase the number of expert judgments required, making DSSs inefficient. The wide spectrum of DSSs developed has curtailed the in-depth study of DSS efficiency.

This paper proposes a systematic codification of DSSs to evaluate their efficiency. The modeling in this paper is based on the identification of the number of judgments required by DSSs in three parts: the information requirements, the quality requirements, and the algorithms. The proposed model obtains four indicators from the latent values of the alternatives (exogenous variables): the expected performance, the percentage of the expected performance over the maximum performance, the maximum admissible cost, and the break-even point. The expected performance is the quantification of what can be expected from the implementation of the DSS. The percentage of the expected performance over the maximum performance indicates whether the DSS leaves much or little room for improvement. The maximum admissible cost is the expected gain over not implementing the DSS and therefore indicates the amount that the total cost should never exceed. Finally, the break-even point indicates the percentage of the maximum achievable performance that can be paid for each expert judgment. This information is essential for the operations manager, as it allows him/her to evaluate his/her decision to implement a DSS a priori (before hiring/purchasing the DSS) by providing guidance on the expected profits and the rates of resources required by each DSS.

The case study shows how to apply the model to two specific DSSs (Ordering and AHP). The results obtained from the analysis of the case study presented in [42] are very impressive and can be used to inform future DSSs. The case study confirmed that DSSs perform better on δ-type problems than on ε-type problems. In δ-type problems, the information obtained is used to select several alternatives, and therefore, greater profit opportunities are presented since more decisions are made. This aspect is also manifested in the fact that DSSs contribute more above the profit of ignorance in the δ-type problem than in the ε-type problem. The requirement of consistency in a DSS increases its performance, and increasing the complexity also increases the performance of a DSS when it has the same consistency requirement. However, the case study showed that an increase in complexity on its own is not sufficient to guarantee an increase in performance because Ord_{wC} outperforms AHP_{woC} on both ε-type and δ-type problems.

The expected performance is not the only indicator used to evaluate a DSS because it does not consider the cost of implementing the DSS. The efficiency of a DSS, as measured by the break-even point, which is the ratio of the maximum cost per expert's judgment to the maximum performance, has been proposed as an alternative indicator instead. The most striking conclusion from the case study indicates that the AHP with consistency is the most efficient DSS on the δ-type problem but the least efficient on the ε-type problem. This "confirms and contradicts" the intuitions expressed in [42] about how "very poor profit percentages can lead to contradictory results depending on the problem posed."

The analysis of the efficiency does not coincide with that of the performance, because the costs show different patterns for different DSSs. The case study shows the importance of not only establishing information requirements and quality requirements but also evaluating their efficiency in different scenarios and problems. This approach emphasizes the importance of elements external to the DSSs, calling for more research into the scenarios and types of problems that a priori determine the efficiency of the different DSSs. Indeed, the results obtained in this study call into question many of the efforts made by the scientific community on the efficiency of DSSs since these efforts do not account for their cost, which is shown herein to be a promising line of research in evaluating the complex DSSs developed in recent years.

7.1. Limitations and future research

The main limitation of the proposed model is the enormous computing power that it requires. The sample space is very large, and the model must calculate all *combinations of judgments* and the probability of each of them. Thus, as the number of alternatives increases, the number of *combinations* increases exponentially. Another limitation of the proposed model is that the conceptual framework of bounded rationality is not the most widely used, and therefore its use requires an entry cost to understand its philosophy. In addition, it requires a conceptual depth to be maintained that does not later translate into algebraic complexity. However, we believe that the framework of bounded rationality provides an opportunity given the enormous efforts in the computer industry to increase the computational power of hardware.

In any case, the proposed efficiency model allows the comparison of different DSSs (with different requirements on the number of judgments, different quality requirements, etc.), and it facilitates the analysis of DSSs in different scenarios (distribution of alternative performances) to evaluate their sensitivity to the decision problem. It also allows one to compare different paradigms, such as holistic versus pairwise evaluation, and determine in which scenarios it is better to use a particular DSS. It provides the opportunity to make modifications to parts of the DSS (e.g., requiring or not requiring consistency) and analyze whether this improves or worsens the DSS's efficiency. From our point of view, the proposed model opens a wide range of new and promising future lines of research.

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CRediT authorship contribution statement

Chiclana Francisco: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Sáenz Royo Carlos:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests. Carlos Saenz Royo reports financial support, administrative support, article publishing charges, equipment, drugs, or supplies, travel, and writing assistance were provided by Spanish Ministerio de Economía y Competitividad. Carlos Saenz Royo reports financial support, administrative support, article publishing charges, equipment, drugs, or supplies, travel, and writing assistance were provided by Diputación General de Aragón (DGA) and the European Social Fund. Carlos Saenz Royo reports financial support, administrative support, article publishing charges, equipment, drugs, or supplies, travel, and writing assistance were provided by Spanish State Research Agency. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

No data was used for the research described in the article.

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