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THIRD-PARTY LIBRARY SELECTION IN IT PROJECTS UNDER IMPERFECT DATA USING DEMPSTER–SHAFER THEORY

This study focuses on a method for selecting third-party libraries for IT projects, which involves systematizing evaluation criteria and applying Dempster–Shafer theory of evidence to model imperfect data. Imperfect data refer to incomplete, contradictory, unreliable, uncertain, imprecise, or ambiguous information. The ***goal*** *is to enhance the validity and reliability of library selection and replacement decisions in the ever-changing landscape of modern projects while also minimizing associated risks. The* ***tasks*** *to be solved include: providing a systematic classification of evaluation criteria that comprehensively characterize third-party libraries; developing a selection method of third-party libraries that incorporates evaluations as imperfect data; integrating and combining evaluations from multiple heterogeneous sources; and demonstrating the application of the proposed method through an illustrative example that establishes confidence intervals for alternative libraries. The* ***methods*** *used are based on the Dempster–Shafer theory of evidence for modeling imperfect data and the Dubois–Prade disjunctive consensus rule for combining evaluations from independent sources. The* ***results*** *show that the proposed approach transforms subjective and imperfect evaluations into evidence, combines them according to the selected rule of evidence theory, and derives confidence intervals that express both guaranteed and possible degrees of support for each library alternative. This study confirms the effectiveness of applying Dempster–Shafer theory of evidence in multi-criteria decision-making contexts that resemble real-world project environments.* ***Conclusions****. The scientific novelty of this study lies in proposing, for the first time, a method for selecting third-party libraries based on the Dempster–Shafer theory of evidence, distinguished by a systematic taxonomy of evaluation criteria, including risk factors, and by combining evidence in support of candidate tools using the Dubois–Prade disjunctive consensus rule. The developed method extends the analytical capabilities of project decision-support systems by enabling comprehensive evaluation and risk-informed selection of third-party libraries in complex, dynamically evolving technological environments.*

Keywords: *third-party libraries; migration; multi-criteria decision-making; method; criteria systematization; Dempster–Shafer theory.*

1. Introduction

The selection of third-party libraries is an essential and recurring task in IT projects, especially when considering their replacement. Third-party libraries include libraries, frameworks, services, and software development kits (SDKs) developed by external providers. These libraries can enhance [1, 2] or simplify the functionality of IT projects. By integrating them as dependencies, developers can utilize ready-made solutions rather than building everything from scratch. This approach accelerates development [3, 4], reduces costs [5], and improves product quality [6].

As the reliance on external libraries has grown, the decision-making process for their selection has evolved from a straightforward technical assessment to a complex challenge involving multiple criteria. This process requires the evaluation of various technical, human, and economic factors, along with associated risks and uncertainties [7]. Choosing an unsuitable library can not only diminish the quality of the final product but also significantly increase development and maintenance costs, introduce severe security vulnerabilities, and jeopardize the project’s long-term success.

1.1. Motivation

The importance of this issue is underscored by monitoring the number of published artifacts in the Maven Central Repository, which represents compiled libraries or modules of third-party libraries [8] (Fig. 1). The data demonstrate a growing trend in the volume of new or updated libraries and modules integrated into projects as third-party dependencies. This trend necessitates not only the regular updating of libraries already used in projects but also the consideration of completely replacing them. Extensive updates and adoptions heighten competition among libraries,

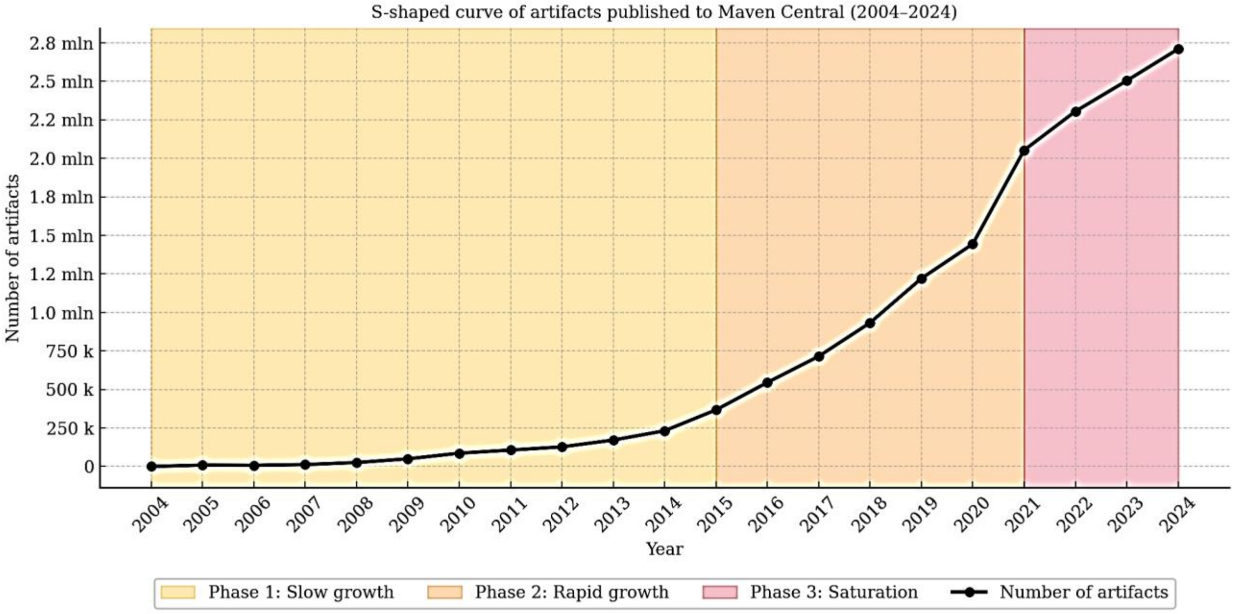

Fig. 1. Growth dynamics of published third-party library artifacts in Maven Central (2004–2024)

complicating the selection process and requiring a systematic, well-founded decision-making approach. Unlike routine updates, replacing a third-party library often necessitates a reevaluation of the system architecture, code modifications, additional testing, and team retraining, which can increase project risks.

This observation is further supported by findings from more than 20 studies [9], which emphasize that the process of replacing third-party libraries in IT projects remains a topic of ongoing debate. Although research in this area is ongoing, its findings remain fragmented and incomplete, underscoring the need for further refinement and systematization of the field.

IT project teams encounter various potential risks when selecting third-party libraries [6]. Failing to recognize or properly assess these risks can result in delays, increased costs [6], maintenance challenges [10], or even the complete replacement of the library [11].

Adopting a formalized approach for evaluating third-party libraries using a defined set of metrics is advisable to mitigate such negative outcomes. A classification of technical criteria relevant to library selection has been outlined in a previous study [12]. A comprehensive analysis that incorporates technical, human, and economic metrics, along with risk assessments and data from multiple sources, can significantly enhance the validity of decision-making. Developing a method that integrates these elements to aid in the selection process is both a timely scientific challenge and a practical necessity, especially given the rapidly changing landscape of modern third-party libraries.

1.2. State of the art

In study [12], the technical factors that significantly influence the selection of a third-party library, especially during replacement, were examined in detail. These factors were represented as a set of technical metrics (criteria) that provided a foundation for a formal evaluation and decision-making process to identify the optimal alternative. This evaluation method was further developed into a selection approach based on the multi-criteria TOPSIS method [13]. This approach enables ranking alternatives based on their proximity to an ideal solution, determined by explicitly defined weights and metric values.

However, this method relies on precise data, which can pose a significant limitation in real-world scenarios. In software development practice, obtaining accurate metric values is often challenging, and sometimes even impossible, due to limited access to information, ambiguity in usage contexts, and the subjectivity or inconsistency of expert evaluations.

Fuzzy numbers can be used within the TOPSIS method to address these challenges; however, they do not adequately model data imperfections. This highlights the need for alternative hypotheses or approaches to solve multi-criteria problems, allowing for the modeling of uncertainty and conflicting assessments in a different manner. Such approaches would provide broader opportunities for adaptation to real-world decision-making scenarios.

In addition to technical factors, contemporary scientific and applied studies emphasize the importance of human and economic factors [6, 9], which together offer a more comprehensive understanding of influences on the selection process of third-party libraries. The economic factor, particularly the risk component, should be given special attention, as it can significantly impact the final decision. For instance, risks [6] related to the likelihood of discontinued support, vulnerability history, update frequency, and developer activity level may influence confidence in selecting a particular library, provided that these risks are adequately assessed.

Notably, risk-related data often come from heterogeneous sources, complicating their interpretation and requiring specialized methods for aggregation and analysis. In existing research [6], risks are generally considered at a high level as a single metric; therefore, referring to more systematic sources for detailed specifications would be beneficial. A relevant list of risks can be derived, for example, from the existing study [14], which outlines typical categories of risks applicable to IT projects and aids in informed decision-making.

Issues such as data incompleteness [15], conflicting evaluations from practitioners and experts across different sources [15], metric uncertainty, and the lack of clear interpretation of metric values [16] are frequently observed when selecting third-party libraries. Although attempts have been made to adapt classical methods to address these challenges, particularly through the use of fuzzy logic, this area has become saturated with research, and further studies involving fuzzy extensions do not always yield novel findings or practically significant conclusions.

Classical probability theory has notable limitations regarding modeling epistemic uncertainty [7] – uncertainty that stems from imperfect or a lack of knowledge and is influenced by the analyst's evaluation. This type of uncertainty is often referred to as subjective uncertainty.

As highlighted by the authors in [7], traditional probabilistic methods used to represent epistemic (or subjective) uncertainty are generally associated with the Bayesian approach. However, these methods require the analyst to have complete information about all considered events' probabilities. In situations where such information is absent, a uniform distribution function is often employed based on Laplace's principle of insufficient reason, which states that all elementary events lacking precise probability estimates should be regarded as equally likely.

In the context of selecting third-party libraries, uncertainty often presents itself in ways that cannot be formally or precisely described. These circumstances limit the effectiveness of classical probabilistic approaches. Formulating well-founded probabilistic estimates of risks or benefits becomes challenging when dealing with new or insufficiently studied libraries, further questioning the relevance of classical approaches.

Given this situation, exploring new strategies for multi-criteria analysis that can handle imperfect data from various sources is crucial. Dempster–Shafer theory of evidence [7] is a promising theoretical framework for developing such an approach, enabling the use of partial confidence assessments while explicitly acknowledging uncertainty and knowledge gaps.

Dempster–Shafer theory can be effectively applied to optimization problems, especially when the problem involves modeling uncertainty, merging information, or making decisions based on imperfect information. This theory provides a mathematical framework for representing and combining uncertain evidence.

Dempster–Shafer theory is a mathematical representation of evidence that serves as an alternative to classical probability theory for dealing with uncertainty. Its core concept focuses on sets of possible events rather than individual events. A key distinction from classical probability theory is that belief mass (or "probabilistic weight") can be assigned not only to individual basic events but also to entire sets of them. This feature enables more flexible modeling of situations where information is imperfect. The theory enables the use of granular knowledge, degrees of belief, and plausibility measures, which are particularly useful in scenarios with uncertain alternatives.

Additionally, Dempster–Shafer theory facilitates modeling situations where information is imperfect, clearly distinguishing between what evidence supports and what is merely possible due to a lack of information. One of its significant strengths is its ability to handle varying levels of information precision without imposing additional assumptions. It also allows for the direct representation of uncertainty in hypotheses. In cases where input data or evidence is imprecise, this uncertainty can be expressed as a set or interval, and the resulting outputs are likewise represented as sets or intervals [7].

Within a finite discrete space, Dempster–Shafer theory serves as an extension of classical probability models, allowing weights to be assigned not only to individual events but also to entire subsets of hypotheses. In traditional probability theory, evidence is exclusively linked to a specific event; however, Dempster–Shafer approach enables evidence to associate with multiple alternative hypotheses simultaneously [7]. When sufficient data are available to estimate the probabilities of single events, this model simplifies to the classical probabilistic interpretation.

The application of Dempster–Shafer theory offers several advantages:

1. It allows for the formalization and aggregation of library evaluations, even when these evaluations contradict each other. This capability enables the combination of different opinions and helps identify the

alternative with the highest confidence level.

2. The theory can handle imperfect evaluations without the need for additional assumptions. In situations where there is uncertainty about replacing an existing library with a new one, the degree of uncertainty and associated risks can be assessed.

3. Dempster–Shafer theory aids in detecting and managing conflicts between different information sources. For example, if one expert deems a library optimal while another considers it obsolete, the theory can help determine the relative weight of these differing assessments.

Overall, the use of Dempster–Shafer theory of evidence allows for a more adaptable approach to formulating problems related to third-party library selection in modern IT projects, which are characterized by uncertainty, dynamism, and a variety of data sources.

1.3. Objectives and approach

This study aims to improve the justification and reliability of decision-making when selecting third-party libraries. Additionally, it seeks to reduce the risk of erroneous or subjective choices arising from multi-criteria evaluations and imperfect data. This will be achieved through the development of a selection method based on Dempster–Shafer theory of evidence.

To achieve this aim, several interconnected objectives have been established:

1. Compile a relevant set of metrics to evaluate third-party libraries.
2. Develop a selection method for third-party libraries that uses Dempster–Shafer theory of evidence while considering the input data imperfections.
3. Provide an example of how the proposed method can be applied by using test data to simulate the decision-making process.

1.4. Outline

The remainder of this study is organized as follows. Section 2 introduces the proposed method, including the systematization of criteria, the application of Dempster–Shafer theory to the optimization task of third-party library selection, the construction of mass functions, the choice of an evidence combination strategy, and the procedures for determining confidence and making final decisions. This section also illustrates the method through a practical example and discusses the interpretation of confidence intervals in decision-making. Section 3 presents the results and discussion, highlighting the method’s advantages and limitations. Finally, Section 4 provides concluding remarks, emphasizes the practical significance of the findings, and suggests directions for future research.

This study’s original contribution begins with the development of an extended and systematized criteria set for third-party library selection, including the integration of risk-related criteria, and continues with the formulation of a selection method based on Dempster–Shafer theory for imperfect data. Thus, the literature review provides the conceptual basis, whereas the criteria systematization, transformation of evaluations into evidence, evidence-combination strategy choice, and decision-making procedure constitute the authors’ original methodological contribution.

2. Method

2.1. Systematization of the selection criteria

To ensure an objective decision-making process when selecting a third-party library from multiple alternatives, a system of criteria (Table 1) that provides quantitative indicators and safeguards the selection’s validity should be used.

Studies [6, 9] have thoroughly examined the factors influencing this choice, offering valuable data that helps prevent biased decisions, which could lead to suboptimal outcomes [17, 18]. The authors [6, 9] categorized the factors considered by practitioners into three main groups: technical, human, and economic. For each factor, a set of criteria was proposed that can either serve as benchmarks for selecting third-party libraries or as a foundation for enhancing the decision-making process.

The list of technical criteria in the existing study [12] was further expanded. The classification of individual criteria into their respective categories was reinterpreted in this study, providing a more comprehensive framework that includes not only technical aspects but also human and economic considerations. A significant portion of these criteria was reformulated to better reflect their essence in the context of the library selection task.

Drawing on recommendations from competitiveness analysis [19], additional technical and economic criteria were introduced. Some of these new criteria were developed by comparing them to those presented on the Gartner Peer Insights portal [20], while others emerged from transforming the risk categories outlined in [6] into evaluation criteria, as structured in [14]. Furthermore, the authors of this study proposed several additional criteria.

A previous study [12] introduced a specification for evaluating criteria (excluding risks) using a unified value scale. It is essential to weigh the benefits of using a library against the potential risks that may arise during or after its integration into a project.

Table 1

Systematized list of criteria influencing library selection

Type	Factor	Criteria
Technical	Project development area	– Compatibility with other libraries, – Alignment of library novelty with the project's innovation level, goals, and objectives.
	Library functionality	– Library size, – Functional alignment with project goals and objectives, – Cross-platform support.
	Library quality	– Alignment with project architecture, – Usability, – Maturity of documentation level, – Security level, – Performance, – Testability, – Resilience to failures, – Quality of warranty and post-warranty service.
	Library release	– Support activity, – Maturity and stability, – Release frequency, – Development roadmap and strategic vision.
	Risk	– Undefined boundaries of integration and the tasks addressed by the library.
Human	Library community	– Experience of use, – Popularity, – Developer rating.
	Organization	– Alignment with corporate culture and policies, – Opportunity to engage specialists for library maintenance.
	Development team	– Consensus on library selection, – Experience of use, – Knowledge and perception, – Learning complexity, – Team competence.
	Risk	– Lack of employee engagement in the project.
Economic	Resources	– Benefit from use (if measurable, return on investment), – Required integration time, – Costs of use and integration, – Licensing and ownership costs, – Ease of purchase conditions.
	Market	– Library brand, – Market prevalence of the library, – Attractiveness to consumers.
	Risks	– Country of origin of the library, – Vendor/producer organization, – Project cost overruns relative to planned budget, – Unfavorable cash flow profile, – Lack of customer approval for financing, – Required investments exceed expected profit, – Unrealistic integration deadlines.

Table 1 was constructed as a result of a multi-stage systematization procedure rather than by directly reproducing an existing classification from the literature. First, previous studies were analyzed to identify the principal groups of factors influencing the selection of third-party libraries and to compile an initial, incomplete set of criteria. Next, these criteria were then reconsidered: some were reformulated, some were redistributed across groups and factors, and duplicated items were eliminated. Additional criteria were then introduced based on structured risks and the authors’ own synthesis. Table 1 presents an extended and systematized criteria system proposed for third-party library selection rather than a direct summary of prior publications.

To effectively assess the risks associated with integrating third-party libraries in a project, using a probability-impact matrix for each type of risk is advisable [21]. This tool enables the determination of risk levels based on two key parameters: the probability of the risk event occurring and the degree of its impact on the project’s objectives and goals. The risk level is calculated by multiplying these two parameters as follows:

$$\text{Risk Level} = \text{Event Probability} \times \\ \times \text{Event Impact}. \qquad (1)$$

The use of the matrix enables several key applications: it facilitates risk prioritization, assesses the appropriateness of resource allocation to the most critical threats and opportunities, and establishes a strategy for responding to identified risks.

The matrix (Table 2) is organized along two axes: the X-axis represents the degree of risk impact and the Y-axis represents the probability of occurrence. Each cell within the matrix corresponds to a specific level of risk; the higher the value, the greater the response priority. Risk levels can be visualized using a color palette to facilitate interpretation and prioritization. Value intervals define the boundaries between the probability and impact scales, which can be flexibly adjusted based on the specifics of the project or the nature of the risks involved.

Table 2 presents an example of a probability-impact risk matrix used in this study as an auxiliary instrument for risk quantification and prioritization rather than as a novel result.

2.2. Library selection approach based on Dempster–Shafer theory of evidence

It is possible to define a set of alternative options when selecting third-party libraries, which is referred to as the frame of discernment in theoretical terminology. For instance, let us define $\Theta = \{A, B, C\}$, representing all possible mutually exclusive hypotheses regarding a particular library’s suitability.

The frame of discernment Θ allows forming the power set of hypotheses $P(\Theta)$, where the subsets represent support for individual alternatives or their combinations (particularly in cases of uncertainty modeling) considered for integration into a project:

$$\mathrm{P}(\Theta) = \{\emptyset, \mathrm{A}, \mathrm{B}, \mathrm{C}, \mathrm{AB}, \mathrm{AC}, \mathrm{BC}, \mathrm{ABC}\}, \qquad (2)$$

where AB indicates uncertainty in choosing between A and B; and ABC denotes complete uncertainty in the selection.

Table 2

Example of a probability–impact risk matrix [21] exclusively focusing on threats

Probability	Negative Impact				
	Minimal 0.05	Low 0.10	Medium 0.20	High 0.40	Critical 0.80
Critical 0.90	0.05	0.09	0.18	0.36	0.72
High 0.70	0.04	0.07	0.14	0.28	0.56
Medium 0.50	0.03	0.05	0.10	0.20	0.40
Low 0.30	0.02	0.03	0.06	0.12	0.24
Minimal 0.10	0.01	0.01	0.02	0.04	0.08

To evaluate each alternative based on criteria and risk levels, a set of information sources $I = \{i_1, \dots, i_n\}$. These sources may include evaluations from the development team, prior experience from experts, conclusions drawn by independent analysts, and feedback from other developers.

For each information source i, the degree of belief should be allocated among all possible hypotheses in $P(\Theta)$ through a mass function (or basic probability assignment) m_i. Imperfect information from a source can be used to support a combined hypothesis. The degree of support ranges from 0 to 1, characterizing the confidence in the corresponding hypothesis; these values can be interpreted as weights of evidence in favor of those hypotheses.

The mass function $m_i: P(\Theta) \to [0,1]$ must satisfy the following conditions:

$$\begin{cases} m_i(\emptyset)=0 \\ \sum_{H \in P(\Theta)} m_i(H) = 1 \end{cases}. \qquad (3)$$

The mass function $m_i(A)$ allows us to determine the degree of confidence or belief assigned to the hypothesis that a specific alternative $A, A \subseteq \Theta$, is the most suitable library for integration, while not supporting any other hypotheses (Fig. 2). The degree of belief reflected in the evidence can be reasonably interpreted as the weight of that evidence.

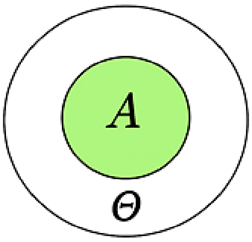

Fig. 2. Inclusion of a subset A within the frame of discernment Θ, where $A \subseteq \Theta$

2.3. Strategy selection for combining evidence

Dempster–Shafer theory of evidence provides a mathematical framework for representing and combining evidence. Evidence obtained from multiple sources should be aggregated using one of the methods listed in reference [7], although this list is not exhaustive.

To combine evidence from different sources I, we might apply the classical Dempster rule of combination (4). According to this rule, the products of mass functions for all possible pairs of hypotheses, one from each source, are first calculated. To determine the aggregate mass assigned to a specific hypothesis A, only those products for which the intersection of the initial hypotheses is exactly equal to A are summed (Fig. 3). This process reflects the search for agreement among the sources.

$$\sum_{\substack{X,Y \in P(\Theta) \\ X \cap Y = A}} m_1(X) \cdot m_2(Y), \qquad (4)$$

where X represents a subset of hypotheses chosen by the first source, and Y denotes a subset of hypotheses selected by the second source.

In the final stage, normalization is applied (5). The mass associated with conflict, specifically, the mass linked to hypothesis pairs with an empty intersection – is calculated as the coefficient K.

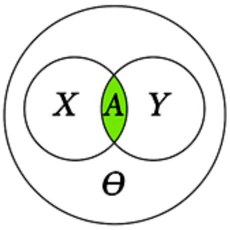

Fig. 3. Intersection of subsets X and Y that constitutes set A, with $X \cap Y = A$

If $K = 1$, it indicates that the sources are in complete conflict and cannot be combined. On the other hand, if they can be combined, the results of evidence aggregation are divided by the normalization coefficient $1 - K$. This process enables the conflict to be completely disregarded and redistributes the masses so that their total once again equals 1.

$$m(A) = \frac{\sum_{\substack{X,Y \in P(\Theta) \\ X \cap Y = A}} m_1(X) \cdot m_2(Y)}{1-K}, \qquad (5)$$

$$K = \sum_{\substack{X,Y \in P(\Theta) \\ X \cap Y = \emptyset}} m_1(X) \cdot m_2(Y). \qquad (6)$$

Combining evidence using alternative methods [7] is advisable rather than relying on Dempster rule of combination. This is because the latter may produce unintuitive results in high-conflict situations. Specifically, contradictory information can be "washed out" during normalization, leading to excessive or even absolute confidence in a single alternative while diminishing overall informativeness. Notably, the list of methods presented by the authors in [7] is not exhaustive; numerous other methods that can effectively address specific tasks based on their unique conditions exist. Moreover, new methods are introduced each year, further expanding the available toolkit.

When the value of K is high, Dempster rule of combination strongly normalizes the remaining probabilities, leading to incorrect conclusions by attributing excessive confidence to one option. Therefore, this method is primarily suitable for situations in which the information sources are largely consistent, and the level of conflict is low.

Alternative methods can help resolve conflicts and are designed for specific contexts, depending on the conditions under which they are applied. A brief description of the methods referenced by the authors in [7] is provided below.

The discount and combine method initially reduces the weight of evidence from each source based on the degree of confidence assigned to it. This step reduces the influence of unreliable sources, requiring a qualified analyst to evaluate each source's reliability. After discounting, the remaining evaluations are combined using one of the most commonly established combination rules, the Dempster rule of combination. This method is applicable in scenarios where the reliability of sources varies (e.g., when expert ratings or historical trust coefficients are available), some sources are suspected to be unreliable, or significant conflict exists between sources.

Yager's modified Dempster's rule does not normalize conflicting information; instead, it treats it as uncertainty and fully incorporates it into the universal set. A high level of conflict is explicitly viewed as an indicator of ignorance, incompatibility, or divergence between sources. This method is useful when highlighting rather than concealing conflict is essential, allowing for monitoring and control of its manifestation as a sign of data inconsistency and lack of consensus.

Inagaki's unified combination rule allows adjusting the amount of conflict considered using a specific coefficient. It essentially combines principles from Dempster's rule and Yager's modified Dempster's rule. When the coefficient is set to zero, it follows Yager's rule; higher values lean toward Dempster's rule. This creates a continuum of possibilities, enabling fine-tuned control over the method's behavior. It is particularly useful for determining which aspects of conflict should be treated as noise and which as potentially valuable knowledge. The method requires an analyst's expertise to justify the appropriate choice of coefficient value.

Dubois–Prade's disjunctive consensus rule [22] focuses on aggregating all evidence from different sources, including conflicting evidence, without suppressing contradictions or forcing agreement. Rather than seeking a single correct alternative, composite hypotheses that include all potentially valid viewpoints are created. Although this rule results in less precision, it is more cautious because it does not discard any alternatives. This rule has low selectivity – it does not provide a definitive choice but instead gathers all possible options. In cases where multiple conflicting sources are present, the result may become overly complex and diffuse. Dubois–Prade's disjunctive consensus rule is suitable when preserving potentially valuable information is more critical than eliminating conflicts between sources. It is especially relevant when at least one source may be reliable but it is unclear which one. This rule is particularly beneficial in practical scenarios, such as when significant discrepancies exist among sources, where retaining all possible alternatives for subsequent analysis or clarification is essential.

Didier Dubois and Henri Prade made significant contributions to the development of a hybrid combination rule [23], which merges the conjunctive approach (similar to Dempster's rule) and the disjunctive approach (as seen in Dubois-Prade's disjunctive consensus rule) based on the level of conflict between sources. When the sources are not in conflict, a conjunctive combination is used to maintain the clarity and precision of the results. In contrast, a disjunctive combination is employed when a conflict arises, but only for the conflicting items of evidence. This strategy helps avoid the loss of valuable information while preserving the conjunctive combination for consistent evidence. This balanced rule preserves precision when data are consistent, while ensuring comprehensive information in instances of conflict. Thus, the hybrid rule represents an evolutionary improvement over the purely disjunctive approach, aiming to minimize excessive uncertainty and enhance flexibility.

Zhang's center combination rule enables the cautious integration of all sources, even in conflict situations, resulting in a single, coherent outcome that reflects conflict information. This method considers the degree of similarity or agreement between the sets of alternatives. However, evaluating intersections—whether by the number of elements or the length of an interval, may be subjective, requiring the expertise of a qualified analyst for proper calibration.

The mixing or averaging method relies on simple averaging, overlooking explicit conflict management and the relative reliability of sources. Conflict is automatically resolved through averaging, making it suitable only when the sources are equivalent and non-contradictory. This method is appropriate when all sources carry equal weight and a differentiated assessment is not required.

Considering the information presented, Dubois–Prade's rule (whether disjunctive consensus or hybrid) is especially suitable for selecting third-party libraries because of the following:

- the information comes from diverse and often conflicting sources, and the method can flexibly process both consistent and conflicting evidence in a flexible manner;
- the method does not normalize conflicts among sources, preventing the artificial boosting of confidence

in an alternative supported only by a subset of sources;

- composite hypotheses provide a natural means to represent uncertainty regarding risk, particularly when identifying a single risky alternative is difficult. The method encourages cautious and conservative decision-making, which is crucial in contexts characterized by imperfect information, conditions that are common when evaluating third-party libraries in complex project environments.

2.4. Combination of evidence without loss of initial information

Dubois–Prade's disjunctive consensus rule is a technique for aggregating evidence, in which the outcome of the combined mass function is confined to the subset of the union of hypotheses (Fig. 4). This approach increases uncertainty while ensuring that no information is lost. The classical formulation of the combined mass function m, when merging two sources, is defined as follows [7]:

$$\mathrm{m(A)} = \sum_{\substack{\mathrm{X,Y \in P(\Theta)} \\ \mathrm{X \cup Y = A}}} \mathrm{m_1(X) \cdot m_2(Y)}, \qquad (7)$$

where X represents a subset of hypotheses chosen by the first source, while Y denotes a subset of hypotheses selected by the second source.

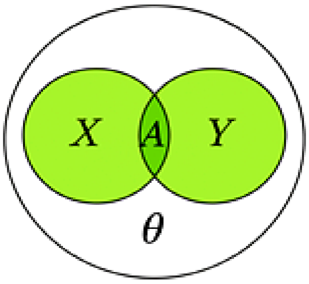

Fig. 4. Union of subsets X and Y is represented as $\mathrm{X \cup Y = A}$.

It is important to note that the method operates in the same way as with two sources when dealing with three or more sources; it is simply expanded to consider all n-ary combinations. We can formally describe the combined mass function m for any number of sources n, where, for a given criterion, information about the instrument is provided by n sources:

$$\mathrm{m(A)} = \sum_{\substack{\mathrm{X_1, X_2, \ldots, X_n \in P(\Theta)} \\ \mathrm{X_1 \cup X_2 \cup \ldots \cup X_n = A}}} \prod_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{m_i(X_i)}, \qquad (8)$$

where $\mathrm{X_i}$ represents the subset of hypotheses regarding the support of A from source i.

2.5. Determining confidence in decision-making

After combining the evidence from each library (alternative), we obtain the mass function m. Based on this mass function, the belief function Bel(A) and the plausibility function Pl(A) are defined.

The belief function Bel(A) characterizes the minimum guaranteed degree of confidence or support for alternative A. In other words, it represents the body of evidence that unequivocally supports hypothesis A.

$$\mathrm{Bel(A)} = \sum_{\mathrm{X|X \subseteq A}} \mathrm{m(X)}, \qquad (9)$$

where X is a subset that is fully contained within A.

The plausibility function Pl(A) indicates the maximum possible degree of confidence or support for A. This includes all evidence that does not contradict A. In other words, it shows that there exists at least one assertion is consistent with the support of A.

$$\mathrm{Pl(A)} = \sum_{\mathrm{X|X \cap A \neq \emptyset}} \mathrm{m(X)}, \qquad (10)$$

where X represents all subsets that intersect with A.

2.6. Decision Making

Decision-making involves a thorough analysis of the confidence interval $\mathrm{[Bel(A), Pl(A)]}$ for each hypothesis A. The width of the interval $\mathrm{Pl(A) - Bel(A)}$ directly reflects the level of uncertainty: a wider interval indicates imperfect evidence, making the conclusions less reliable.

Special attention is given to the belief function Bel(A). If $\mathrm{Bel(A) = 0}$, it clearly signifies the absence of direct evidence supporting the hypothesis. In this case, the plausibility Pl(A) is entirely derived from indirect support, such as evidence favoring a combined hypothesis AB.

The final decision is typically made by comparing hypotheses based on two main criteria. The hypothesis with the highest Bel(A) represents the most cautious and reliable choice. Conversely, choosing the hypothesis with the highest Pl(A) reflects an optimistic approach because it considers all evidence that does not contradict the hypothesis.

The interpretation of these intervals can be found in the section titled "Samples of Confidence Intervals" (Table 11).

2.7. Sample

A development team is choosing between three third-party libraries, represented by the frame of discernment $\Theta = \{\mathrm{A, B, C}\}$. The team has defined three criteria to guide their decision-making: technical, human, and economic. They will use two sources of information for evaluation: the official documentation and developer feedback and the conclusions drawn from independent experts.

The team collected and analyzed information from both sources and established a mass function for each, assigning degrees (or masses) of support to the alternatives.

For the first source, which includes information from documentation and developer feedback, the evidence is interpreted as follows (Table 3):

- 70% of the evidence indicates that library A receives high evaluations for functionality and productivity, aligns with expectations, and has comprehensive documentation.
- 20% of the evidence suggests that libraries A and B provide the required functionality; however, their documentation for complex configurations is weak, increasing the risk of prolonged implementation.
- 10% of the evidence reflects uncertainty, indicating that some information from this source does not allow for a clear risk assessment regarding long-term support.

Table 3

The mass function of the first source

Hypothesis	A	AB	Θ
m_1	0.7	0.2	0.1

For the second source, which incorporates expert opinions, the evidence is interpreted in Table 4 as follows:

- 50% of the evidence indicates that experts see A as a reliable choice with a good reputation and low risks of licensing incompatibility.
- 20% of the evidence suggests that experts consider both functional libraries A and B but emphasize greater risks concerning long-term support due to less active community involvement.
- 20% of the evidence reflects that experts regard A and C as the most reliable options regarding long-term support and licensing risks.
- Finally, 10% of the evidence denotes uncertainty because experts cannot always account for all the nuances of a specific project.

Table 4

The mass function of the second source

Hypothesis	A	AB	AC	Θ
m_2	0.5	0.2	0.2	0.1

To calculate the combined belief function from two information sources, their masses must be aggregated. Dubois–Prade's disjunctive consensus rule for combining evidence involves merging all possible hypotheses. This process is performed in a tabular format, as suggested by the authors in [7].

As an example, we demonstrate the computation of the combined mass function for complete uncertainty, denoted as Θ (Table 5). Then, all pairs of hypothesis subsets — one from the first source (with horizontally arranged hypotheses) and one from the second source (with vertically arranged hypotheses) — whose union forms the target subset Θ. The goal is to obtain the combined mass by multiplying the masses of each pair. An alternative notation for $m(\Theta)$ is $m(ABC)$, where the union of subsets AB and AC yields ABC.

Table 5

Calculation of the combined mass function $m(\Theta)$

	$m_2(A)$	$m_2(AB)$	$m_2(AC)$	$m_2(\Theta)$
$m_1(A)$	–	–	–	0.07
$m_1(AB)$	–	–	0.04	0.02
$m_1(\Theta)$	0.05	0.02	0.02	0.01

As in the previous example, the calculation of the combined mass function $m(AB)$ for all pairs of hypothesis subsets whose intersection yields the target subset AB from both sources is presented in Table 6.

Table 6

Calculation of the combined mass function $m(AB)$

	$m_2(A)$	$m_2(AB)$	$m_2(AC)$	$m_2(\Theta)$
$m_1(A)$	–	0.14	–	–
$m_1(AB)$	0.10	0.04	–	–
$m_1(\Theta)$	–	–	–	–

Continuing the computation for all pairs in this manner, we arrive at the final combined masses for each hypothesis, which are summarized in Table 7.

Table 7

Calculation of combined masses
for the mass functions $m_1 \cdot m_2$

	$m_2(A)$	$m_2(AB)$	$m_2(AC)$	$m_2(\Theta)$
$m_1(A)$	0.35	0.14	0.14	0.07
$m_1(AB)$	0.10	0.04	0.04	0.02
$m_1(\Theta)$	0.05	0.02	0.02	0.01

Next, the results are consolidated in Table 8. The total of these masses must equal 1, which serves as a verification that all evidence has been considered. Additionally, the belief level for each hypothesis, denoted as Bel, can be determined based on the mass function m that fully, unambiguously, and exclusively supports each non-composite hypothesis.

The combined masses for the hypotheses also enable us to compute each hypothesis's plausibility (Table 9).

Table 8

Calculation of combined mass sums m and determination of belief function Bel

	A	B	C	AB	BC	AC	Θ	∑
m	0.35	0	0	0.28	0	0.14	0.23	1.0
Bel	0.35	0	0	–	–	–	–	–

Table 9

Calculation of plausibility function Pl

	A	B	C	AB	BC	AC	Θ	∑
A	0.35	–	–	0.28	–	0.14	0.23	1.0
B	–	0	–	0.28	0	–	0.23	0.51
C	–	–	0	–	0	0.14	0.23	0.37

The analysis of the results in Table 10 reveals that library A is the potential optimal choice, as it excels in both key indicators:

1. It is the only option that received direct support after the evidence was combined, indicating a strong belief in library A.
2. The maximum plausibility indicates that none of the available evidence contradicts the hypothesis that library A is the best option.

Table 10

Confidence intervals for libraries

	Bel	Pl
A	0.35	1.0
B	0	0.51
C	0	0.37

However, the wide confidence interval for library A indicates significant uncertainty. Although it appears to be the best candidate, substantial evidence remains ambiguous. There is still an "unknown share" of information that prevents a definitive decision.

At this stage, selecting library A is a logical step. Nevertheless, to minimize risks and enhance confidence, gathering additional evidence to clarify the ambiguous information is advisable.

2.8. Samples of the confidence intervals

Table 11

Interpretation of Confidence Interval Types for Hypothesis H

#	Hypothesis type	Bel(H)	Pl(H)	Interpretation
1	Truth	1.0	1.0	All evidence supports H, Bel(H) = 1. No evidence contradicts H, Pl(H) = 1. No uncertainty, since the interval width equals 0. Hypothesis is proven true. Evidence is precise, as belief and plausibility coincide.
2	Support	0.7	0.8	There is a large amount of direct evidence supporting H, Bel(H) = 0.7. Low uncertainty due to the narrow interval. There is confidence that hypothesis H is highly probable.
3	Uncertainty	0	1	No direct evidence supports H, Bel(H) = 0. No evidence contradicts H, Pl(H) = 1. Nothing is known about hypothesis H due to the wide interval. Hypothesis is possible, but unconfirmed.
4	Contradiction	0.1	0.2	Almost no direct evidence supports H, Bel(H) = 0.1. Most evidence contradicts H, Pl(H) = 0.2. Low uncertainty due to the narrow interval. There is confidence that hypothesis H is highly improbable.
5	Falsity	0	0	No direct evidence supports H, Bel(H) = 0. All evidence contradicts H, Pl(H) = 0. Hypothesis is proven false; it is impossible.

3. Results and Discussion

A method has been developed for selecting third-party libraries that distinguishes itself from existing approaches by comprehensively evaluating alternatives, accounting for input data imperfections, and facilitating the creation of a tailored selection strategy for specific projects. This method employs systematized criteria combined with Dempster–Shafer theory of evidence, along with evidence combination rules modifications.

The proposed method includes the following steps:

1. Define the set of candidate libraries for integration into the project. These candidates form the frame of discernment for further analysis.
2. From the systematized set, select the criteria most pertinent to the specifics and needs of the project to ensure a thorough evaluation.
3. Construct evidence based on expert assessments and information from multiple sources. Assign mass functions to represent the degree of support for various alternatives or their combinations.
4. Use Dubois–Prade disjunctive consensus rule to aggregate the evidence. This enables the integration of heterogeneous evaluations, producing a coherent representation of each alternative's advantages and risks.
5. Calculate the minimum guaranteed level of support (belief) and the maximum possible support (plausibility) for each alternative. This step enables the assessment of both confidence and uncertainty in the decision-making process.
6. Select the optimal library based on the analysis of confidence intervals, paying attention to their width as an indicator of uncertainty.

Based on Dempster–Shafer theory of evidence, this decision-making method enables choices to be made based on confidence intervals for alternatives, even despite significant uncertainty and incomplete knowledge. A key principle of this theory is that confidence in evidence can be allocated not only to a single alternative but also to multiple alternatives simultaneously, with varying degrees of intensity. This enables more flexible modeling in situations characterized by imperfect information, highlighting the theory of evidence's practical value in third-party library selection.

Advantages. Dempster–Shafer theory of evidence simultaneously supports multiple alternatives, represents uncertainty levels, and maintains conflicts between sources without artificially eliminating them. Uncertainty is modeled through the distribution of support across various alternatives in the case of imperfect data. The support can be assigned to sets of alternatives, with any remaining support indicating complete uncertainty. This method enables the mathematical representation of a lack of knowledge without resorting to arbitrary values while preserving conflict information. The input data are kept in their original form rather than averaged, enabling re-analysis under different combinations. Dubois–Prade disjunctive consensus rule considers all alternatives supported by at least one source, resulting in a consensus that reflects all perspectives, unlike approaches that average or discard conflicting evaluations. The method can signal the presence of conflict for further analysis without rushing to a final decision. A confidence interval is created for each alternative; the width of this interval reflects the level of uncertainty, narrow intervals indicate high certainty, while wide intervals suggest significant doubt.

It should be emphasized that the achievement of the study aim is confirmed primarily at the methodological level. The proposed method replaces informal or fragmented reasoning with a structured evaluation procedure based on a systematized set of technical, human, economic, and risk-related criteria and on the formal aggregation of evidence from multiple heterogeneous sources to improve decision-making justification. In this way, the library choice is grounded in an explicit analytical model rather than in isolated opinions. The reliability of decision-making is also improved at the methodological level because the method not only identifies a potentially preferable alternative but also quantifies the guaranteed degree of support through the belief function, the admissible degree of support through the plausibility function, and the remaining uncertainty through the confidence interval width. The risk of erroneous choices is reduced because the method reveals cases in which the available evidence is weak, ambiguous, or insufficiently specified. Thereby preventing overconfident conclusions under imperfect data conditions. Simultaneously, the risk of subjective choices is reduced because individual assessments are transformed into formalized evidence and combined within a unified framework, which limits the influence of uncontrolled personal judgments and makes disagreement and uncertainty explicit.

Disadvantages. Although the theory of evidence is not yet widely applied in practice, its usage is growing rapidly in areas [24], such as risk analysis, fault detection, wireless sensor networks, health state prediction, image processing, and target tracking. However, the computational complexity increases exponentially with the number of alternatives, although modern computational power partially mitigates this issue. Additionally, interpreting results can be challenging due to numerous terminological inconsistencies in the literature, a lack of consensus on fundamental principles, and the less intuitive nature of confidence intervals compared to simple numerical ratings. Furthermore, there is currently no universal standard for evidence combination; several rules exist (e.g., Dempster, Yager, Dubois–Prade, Smets), and the choice depends on the context. This raises concerns about the reproducibility of the results and may complicate the practical applications of the proposed method.

A promising area for future work involves comparing outcomes produced by different combination rules, which could lead to algorithms that automatically select a method based on the level of conflict between sources. The development of methods for determining, collecting, and consolidating confidence at the source level, particularly focusing on justifying support for specific alternatives, could be another area of investigation.

4. Conclusions

The further development of methods for selecting third-party libraries has focused on systematizing a set of technical, human, and economic criteria [6, 9] that influence library choice. This development also includes the integration of risks as evaluation criteria. The classification of criteria by factors and types was reconsidered during this process. A significant number of criteria from previous studies were reformulated to more precisely reflect the selection task, and duplicates that arose after the revised structuring and risks integration were eliminated.

In total, 6 technical criteria, 7 human criteria, and 12 economic criteria were added. Among these, 9 risk-related criteria were transformed from an existing risk classification into evaluation criteria. Of the 21 risks identified in earlier studies [14], only 9 were deemed most relevant, while others were excluded due to content duplication, overlap with already covered criteria, or lack of applicability within the study's context. Consequently, an updated and consistent system of criteria was created, enabling a more comprehensive evaluation of third-party libraries.

For the first time, Dempster–Shafer theory of evidence [7] was applied to the optimal third-party library selection problem under conditions of multi-criteria evaluation, imperfect data, and epistemic uncertainty. Special emphasis was placed on providing a practical explanation of this theory's foundations using a concrete library selection case study. In academic literature, this theory is often presented in a fragmented manner with different approaches and terminology, complicating its understanding and limiting its application in practical research.

The study demonstrated the possibility of transforming criteria into mass functions and combining evidence from various sources using Dubois–Prade disjunctive consensus rule. This approach ensures a flexible interpretation of results, particularly in cases of high conflict, where aggressive normalization may distort conclusions due to classical Dempster's rule.

The developed method allows users to construct confidence intervals for each alternative and assess the level of uncertainty, identify conflicting or ambiguous evaluations and use them as indicators for additional analysis, and support decision-making in situations characterized by multi-criteria requirements, imperfect data, and incomplete knowledge.

The proposed approach's practical value lies in laying the groundwork for developing decision-support systems that can reduce risks when replacing or introducing third-party libraries in real IT projects. Applying the theory of evidence significantly enhances the justification, reliability, and robustness of decisions in the dynamic and uncertain environment of modern software development.

Thus, the achievement of the study aim is confirmed at the methodological level as follows: decision-making justification is improved by replacing fragmented evaluation with a systematized criteria-based and evidence-based procedure; decision-making reliability is improved by quantifying guaranteed support, admissible support, and uncertainty for each alternative; and the risk of erroneous or subjective choice is reduced because the method explicitly reveals conflict, ambiguity, and insufficient evidence instead of masking them.

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Conflict of Interest

Author **Igor Kononenko** is a member of the Editorial Board of this journal. They did not involved in the peer review, handling, or decision-making process for this manuscript

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Data Availability

The data supporting the importance of this study's aim are available in the Maven Central Repository at https://mvnrepository.com/repos/central.

Use of Artificial Intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work. All the authors have read and agreed to the published version of this manuscript.

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ВИБІР СТОРОННІХ ІНСТРУМЕНТІВ РОЗРОБКИ В ІТ-ПРОЄКТАХ ЗА УМОВ НЕДОСКОНАЛИХ ДАНИХ ІЗ ВИКОРИСТАННЯМ ТЕОРІЇ ДЕМПСТЕРА—ШАФЕРА

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Предметом дослідження є метод вибору сторонніх інструментів розробки для IT проєктів на основі систематизації критеріїв і застосування теорії доказів Демпстера–Шефера для моделювання недосконалих даних. Під недосконалими даними у статті розуміються неповні, суперечливі, ненадійні, невизначені, неточні та/або неоднозначні дані. **Метою** дослідження є підвищення обґрунтованості та достовірності рішень щодо вибору чи заміни сторонніх інструментів у динамічних умовах сучасних проєктів та зменшення ризиків, що супроводжують цей процес. До **завдань** дослідження належать: систематизація класифікації критеріїв оцінювання, які всебічно характеризують сторонні бібліотеки; розроблення методу вибору сторонніх бібліотек, що враховує оцінки як недосконалі дані; інтеграція та об'єднання оцінок із кількох гетерогенних джерел; демонстрація застосування запропонованого методу на прикладі, який визначає довірчі інтервали для альтернативних бібліотек. У дослідженні використано **методи**, засновані на теорії доказів Демпстера–Шефера для моделювання недосконалих даних, а також правило диз'юнктивної згоди Дюбуа–Праде для об'єднання оцінок із незалежних джерел. Отримані **результати** показують, що запропонований підхід перетворює суб'єктивні та недосконалі оцінки з різних джерел на докази, поєднує їх відповідно до обраного правила комбінування доказів і формує інтервали довіри, які відображають гарантовану та можливу підтримку альтернатив. Дослідження підтверджує ефективність застосування теорії доказів Демпстера–Шефера в задачах багатокритеріального прийняття рішень, що відтворюють реальні умови проєктного середовища. **Висновки.** Наукова новизна дослідження полягає у створенні вперше методу вибору сторонніх інструментів розробки на основі теорії доказів Демпстера–Шефера, який відрізняється від існуючих систематизацією критеріїв оцінювання, включно із ризиками, та застосуванням комбінування доказів щодо підтримки інструментів з допомогою методу диз'юнктивної згоди Дюбуа-Праде. Розроблений метод розширює аналітичні можливості систем підтримки прийняття рішень у проєктах, забезпечуючи комплексну оцінку та вибір інструментів з урахуванням ризиків у складних і динамічно змінюваних технологічних середовищах.

Ключові слова: сторонні інструменти розробки; міграція; багатокритеріальне прийняття рішень; метод; систематизація критеріїв; теорія доказів Демпстера-Шейфера.

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