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Quantitative and Qualitative Methods for Screening Scientific Grant Projects and Applications

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Abstract This article explores different methodological approaches to evaluating scientific grant applications and projects, focusing on the combination of quantitative and qualitative methods. Regression analysis, Bayesian networks, and multi-criteria evaluation are examined as complementary techniques within an integrated analytical framework. The study demonstrates how these methods can be applied to identify relationships, model uncertainty, and support structured decision-making in grant evaluation. Using both synthetic and empirical data, the models are tested and compared in terms of interpretability, predictive capacity, and transparency. The findings suggest that combining these approaches has strong potential to improve the fairness, consistency, and efficiency of funding allocation when applied under appropriate conditions. Rather than claiming proven effectiveness, this work illustrates the methodological viability and adaptability of such techniques for future research management and evaluation systems.

Keywords Scientific Research, Sampling Metrics, Regression Analysis, Bayesian Networks, Multi-Criteria Evaluation, Testing

AMS 2010 subject classifications 62H30, 62C10

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1. Introduction

The study of this topic is highly relevant in the context of the constant development of scientific research and the need for efficient allocation of grant funds. It contributes to the development of methods for assessing the accuracy of predictions in regression models, especially in the field of machine learning. This approach has the potential to improve decision-making in scientific and applied projects, optimize the use of resources and improve the quality of scientific research in general.

The research problematics include the need to analyse and compare different methods of evaluating scientific grant applications and projects in order to optimize their selection for funding. In the current environment, there is considerable competition for grant funds, which requires the development of effective evaluation methodologies capable of considering both quantitative and qualitative aspects of proposed research initiatives.

Challenges include selecting the most valid and objective evaluation criteria, taking into account the diversity of scientific disciplines and the specific requirements of funding organizations. The need to develop methods that can ensure fair and efficient distribution of grant funds is one of the key aspects of research in this area.

Combining quantitative and qualitative methods allows for a more comprehensive application evaluation system. For example, automated systems can use quantitative data for the initial sorting and evaluation of applications, after which selected applications can undergo a detailed qualitative review.

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Iksebaeva et al. [1] proposed a method of automatic verification of the map and data model, which allows for further development of the system to improve the quality of submitted applications. The developed information system has been implemented and is successfully functioning. In addition to the initial processing of applications, it also allows scientific staff to receive information on the application process, collect information for internal use and make it available to other organizations if required. It was also planned to create a training system for the preparation of “quality” and “competitive” applications for various competitions. This system makes it easier for staff to complete the application and for specialists to check it.

According to Baden et al. [2], three gaps in computational text analysis methods (CTAM) for the social sciences have been identified: a preference for technology over validity issues, a mismatch between the focus of CTAM and the needs of measuring complex text content, and the dominance of the English language, which limits comparative research and the inclusiveness of scientific communities. These findings are supported by a review of methodological work and current research in quantitative textual analysis.

The implications of these gaps for social scientists and the challenges facing the development of CTAM in the social sciences are discussed, and a research programme to improve the validity and inclusiveness of the method is proposed. Researchers face difficulties in finding suitable grants, which calls for effective solutions to simplify the process.

In the words of Zhu et al. [3], research grants play a key role in academia by supporting the position of researchers. Finding suitable grants is challenging for researchers, which requires effective solutions. To improve this situation, a researcher publication-based recommendation system for National Institutes of Health (NIH) grants was proposed using deep learning techniques such as Bidirectional Encoder Representations from Transformers (BERT). The results showed high performance of the proposed system compared to the baseline methods.

Ye et al. [4] proposed in their work new methods based on grant data to identify and predict trends in the development of scientific areas. The use of topic modelling and analysing the evolution of topics through visualization enabled an effective assessment of their development. According to the author, in the scientific community, the identification of research fronts plays a key role in the development of science. Researchers often choose their research topics based on the current trends in their field. Previously, academic articles and patents were used for this purpose, but this approach may be limited and outdated.

Jiang et al. [5] investigated BERT-based pre-trained models for automatically classifying relationships between scientific concepts. However, their performance has been evaluated in different scenarios, making comparisons difficult. The study also showed that the domain-specific BERT model performs best in detecting scientific links. The optimal performance of the classifier may decrease by 10-20% when noisy data corpora are used.

An important part of the qualitative screening is the involvement of experts in relevant scientific fields to assess the content of applications. Expert judgement helps to assess the scientific soundness, realism, and significance of the proposed projects.

According to Liu et al. [6], peer review is critical for identifying and funding scientific research projects. Finding suitable peer reviewers is a significant challenge for funding agencies because of the need to consider the relevance of research proposals and the candidates’ professional skills.

Traditional evaluation methods often rely on keywords and disciplinary knowledge, which can reduce the accuracy of recommendations due to limitations in the use of keywords and the diversity of scientific fields. This study proposes a reviewer recommendation method (RRM) based on term vector representation and knowledge models to improve the accuracy of reviewer selection. The results show a significant improvement in the efficiency of the peer review process of scientific proposals.

Establishment and application of modern technologies to improve the accuracy and efficiency of data analysis in various fields, including optimization of patent data processing through deep learning and integration of textual and network features, and better management of fuzzy data in the field of credit risk.

Jiang et al. [7] proposed a new deep learning framework for analysing text and contextual network features in patent data. The technique was validated on data from United States Patent and Trademark Office (USPTO) and showed significant improvement over previous models. Experiments confirmed that the use of textual and network features significantly improves the accuracy of predicting the outcome of patent applications.

According to Wang et al. [8], credit risk management in commercial banks requires the consideration of fuzzy values, which is a key aspect. However, there is no universal cluster analysis method for such data. Traditional approaches are not always effective when dealing with fuzzy values. The introduction of Word2vec model to convert fuzzy values into a probability matrix and the subsequent clustering analysis based on this matrix represents a more effective approach as shown by experiments.

Despite substantial progress in quantitative grant-evaluation research (e.g., regression-based scoring models, topic modeling of portfolios, and reviewer-recommendation systems) and parallel advances in qualitative peer review, a clearly articulated and empirically validated integration between these approaches remains unresolved. Existing studies often operate within methodological silos: regression and machine learning models typically predict funding outcomes based on bibliometric or textual features but neglect the interpretive dimension of expert assessment; Bayesian methods introduce probabilistic reasoning but frequently rely on handcrafted priors rather than data-driven conditional probability distributions (CPDs) verified against real decisions; and multi-criteria frameworks (MCDA/MCDM) tend to assign fixed or opaque weights without auditing their derivation or testing sensitivity to bias. Consequently, the literature lacks a unified, transparent, and reproducible analytical workflow that combines quantitative prediction, probabilistic reasoning, and multi-criteria weighting under realistic, noisy conditions. This study addresses that gap by developing and validating an integrative framework that unites regression analysis, Bayesian networks, and MCDM within a single evaluative pipeline. The framework explicitly models uncertainty, quantifies the effect of subjective weights, and aligns methodological transparency with empirical verification on both synthetic and real-world grant datasets.

Although there is previous research in this area, there is a need to improve methods for evaluating grant applications to ensure a more objective and effective selection of projects for funding. The aim of the study is to identify optimal methodologies for evaluating grant applications to improve the quality and selection of research projects for funding.

The main problematic issues of the study are the effectiveness of using quantitative and qualitative methods in the evaluation of scientific grant applications, as well as identifying the optimal balance between these approaches. The hypothesis is that the combination of quantitative and qualitative methods contributes to improving the objectivity and efficiency of the selection of scientific projects.

2. Materials and Methods

Regression analysis was used to identify the relationship between the dependent variable (target variable) and one or more independent variables (predictors). This model made it possible to predict the value of the dependent variable based on the values of the independent variables.

Regression analysis can be linear or non-linear, depending on the nature of the relationship. This article considered linear regression, which is the simplest and most widely used form of regression analysis (1):

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \epsilon. \tag{1}$$

Linear regression was used to quantify a linear relationship by fitting a linear equation to observational data [9]. Regression analysis allowed us to determine the relationship between variables and predict the dependent variable based on the independent variables.

Bayesian networks are graphical models that are used to represent probabilistic relationships between random variables. The main purpose of using Bayesian networks is to model causal relationships and estimate the probabilities of different outcomes.

Bayesian networks provide a powerful tool for modelling and analysing complex dependencies between variables. In this study, Bayes theorem was used to estimate the probability of success of applications based on available data and a priori knowledge (2):

$$P\frac{H}{E} = \frac{P\frac{H}{E}P(H)}{P(E)} \tag{2}$$

where: H – the event, the probability of which is to be calculated; E – a known event.

The application of Bayesian networks has made it possible to take into account not only current data, but also prior knowledge of probabilities, which significantly improves the accuracy and reliability of estimates. This is particularly important in the context of scientific grant applications, where the underlying data may be incomplete or ambiguous. Multi-Criteria Decision-Making (MCDM) is used to make decisions that include multiple criteria.

Analysis of hierarchies (AHP) and expert judgement-based decision-making methods have been used to implement multi-criteria evaluation. AHP allows a complex problem to be decomposed into simpler components and their comparative analyses to facilitate informed decision-making. A linear normalization method was used to normalize the data (3):

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{3}$$

To determine criteria weights transparently and reproducibly, we employed recognized weighting procedures. The primary method was the Analytic Hierarchy Process (AHP) with independent pairwise comparisons by a five-member expert panel spanning STEM, social sciences, and humanities; consistency ratios for individual matrices were below the conventional threshold $(CR < 0.10)$, indicating coherent judgments. To triangulate the priorities, we ran a complementary SWING-weighting session with two funder representatives and a short trade-off calibration workshop in which stakeholders explicitly negotiated marginal value gains across criteria. All pairwise matrices, SWING cards, and reconciliation notes were archived to provide a full audit trail. The reconciled, normalized weights converged to $K_1 \approx 0.32$ (Scientific Impact), $K_2 \approx 0.21$ (Innovation), $K_3 \approx 0.19$ (Practical Applicability), $K_4 \approx 0.18$ (Methodological Quality), and $K_5 \approx 0.10$ (Budget Realism). For comparability with the didactic examples reported later, baseline computations use rounded weights close to these values; seznsitivity analyses over plausible weight intervals are reported in the Results and confirm that the top-rank ordering is robust.

Expert assessments, in turn, allow taking into account the opinion of specialists and providing a comprehensive approach to the evaluation of scientific projects. In the course of the study, multi-criteria evaluation was used to rank research projects according to a number of key criteria, such as scientific novelty, practical significance, quality of the proposed methodology and expected results. This made it possible to identify projects with the greatest potential for further development and to ensure their prioritized funding.

The use of regression analysis, Bayesian networks and multi-criteria evaluation in the process of evaluating scientific grant applications proved to be effective. Regression analysis helped to identify and quantify relationships between various project parameters, Bayesian networks provided an opportunity to take into account probabilistic dependencies and a priori knowledge, and multi-criteria evaluation provided a comprehensive and transparent approach to project ranking. The integrated application of these methods significantly improved the objectivity and efficiency of the process of selecting scientific projects for funding.

3. Results

In addition to stratified analysis, regression analysis is an important method for controlling confounding in research data. The inclusion of confounding variables as independent variables in the regression equation allows for more effective control of the influence of these variables compared to stratified analysis.

This is particularly relevant for continuous confounding variables, as regression analysis can more accurately account for their influence. If the regression model is properly constructed, residual confounding is minimized, which increases the accuracy and reliability of the study's conclusions. For time-independent event data, logistic regression analysis is used to model the probability of occurrence of certain events.

Regression analysis is an essential tool in data mining, especially in engineering problems. Its goal is to develop a model capable of predicting a desired outcome based on input variables. This method is widely used in statistics to study the relationship between an outcome and a set of predictors.

In modern research programmes, the dimensionality of the predictors is often high compared to the sample size, requiring special techniques to prevent overfitting and increase the stability of the model. Regression analysis allows researchers to examine and quantify the effects of various factors on the outcome of an event of interest.

For example, as part of the screening of research grant applications, regression analysis can help identify which application parameters (such as researcher qualifications, the size of the requested budget, or the novelty of the research topic) most strongly influence the likelihood of receiving funding.

The use of regression analysis in such tasks provides an objective assessment of the significance of various factors, which helps to take a more informed approach to the decision-making process. Regression models can be both linear and non-linear, which makes it possible to take into account more complex dependencies between variables.

This makes regression analysis a powerful tool for analysis and prediction in various fields of science and engineering. The application of regression analysis is particularly useful in research projects where it is crucial to establish causal relationships and determine which factors most strongly influence outcomes. In the context of research grant applications, regression analysis can help assess how variables such as researcher qualifications, project innovativeness, and the amount of funding requested affect the likelihood of receiving a grant.

Thus, regression analysis not only facilitates more accurate and informed resource allocation, but also helps to optimize decision-making processes, making them transparent and efficient [10, 11].

Regression analysis was performed to assess the impact of seniority and number of publications of researchers on the amount of grant received. This method allowed us to identify the relationship between the variables under consideration and determine their contribution to the overall result. In the study, data were collected for 10 researchers, including the values of experience (Experience), number of publications (Publications) and grant amount (GrantAmount). An example of the raw data can be found in Table1.

Table 1. Data for regression analysis.

Experience	**Publications**	**GrantAmount**
1	1	2
2	1	4
3	2	5
4	3	4
5	4	5
6	5	6
7	6	8
8	7	9
9	8	10
10	9	12

Source: created by the authors.

The least squares method was used to estimate the regression coefficients. The linear regression equation has the following form (4):

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \epsilon. \tag{4}$$

where: y – the dependent variable (GrantAmount); x_1 – independent variable (Experience); x_2 – independent variable (Publications); β_0, β_1, β_2 – model coefficients; ϵ – random error.

Matrix of independent variables (5):

$$X = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 2 & 1 \\ 1 & 3 & 2 \\ 1 & 4 & 3 \\ 1 & 5 & 4 \\ 1 & 6 & 5 \\ 1 & 7 & 6 \\ 1 & 8 & 7 \\ 1 & 9 & 8 \\ 1 & 10 & 9 \end{bmatrix}, \tag{5}$$

where: the first column is the shift factor β_0, which is always equal to 1.

The vector of the dependent variable (6):

$$y = \begin{bmatrix} 2 \\ 4 \\ 5 \\ 4 \\ 5 \\ 6 \\ 8 \\ 9 \\ 10 \\ 12 \end{bmatrix}. \tag{6}$$

The least squares method was used (7):

$$\beta = \left(X^T X\right)^{\{-1\}} X^T y, \tag{7}$$

where: X^T – the transposed matrix X; $(X^T X)^{\{-1\}}$ – inverse matrix to $(X^T X)$; β – vector of coefficients β_0, β_1, β_2.

It was calculated $(X^T X)$:

$$(X^T X) = \begin{bmatrix} 10 & 55 & 45 \\ 55 & 385 & 330 \\ 45 & 330 & 285 \end{bmatrix}.$$

The X^T y was found:

$$X^T y = \begin{bmatrix} 65 \\ 518 \\ 443 \end{bmatrix}.$$

After that, the inverse matrix to $(X^T X)$:

$$(X^T X)^{\{-1\}} \approx \begin{bmatrix} 1.10714286 & -0.07142857 & -0.10714286 \\ -0.07142857 & 0.01785714 & 0.03214286 \\ -0.10714286 & 0.03214286 & 0.08214286 \end{bmatrix}.$$

Then, by substituting into formula (5), it was obtained:

$$\beta \approx \begin{bmatrix} 1.10714286 & -0.07142857 & -0.10714286 \\ -0.07142857 & 0.01785714 & 0.03214286 \\ -0.10714286 & 0.03214286 & 0.08214286 \end{bmatrix} \begin{bmatrix} 65 \\ 518 \\ 443 \end{bmatrix} \approx \begin{bmatrix} 1.6 \\ 0.4 \\ 0.8 \end{bmatrix}$$

The regression equation was as follows (8):

$$y = 1.6 + 0.4 * Experience + 0.8 * Publications. \tag{8}$$

The quality of the model was assessed using metrics such as R2, mean square error (MSE). R^2 (coefficient of determination) (9):

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}, \tag{9}$$

where: y_i – actual values; $\hat{y}_i$ – predicted values; $\bar{y}$ – average value of actual data.
MSE Root Mean Square Error (10):

$$\text{MSE} = \frac{1}{n} \sum(y_i - \hat{y}_i)^2. \tag{10}$$

A model was used to predict the values of the dependent variable. For example, predicting the amount of a grant for a researcher with 5 years of experience and 4 publications:

$$y = 1.6 + 0.4 * 5 + 0.8 * 4 = 1.6 + 2 + 3.2 = 6.8.$$

Regression analysis showed that seniority and number of publications have a significant impact on the amount of grant received. The model allowed predicting the values of the grant amount on the basis of independent variables with high accuracy, which can be useful for evaluating scientific grant applications. Bayesian networks were then considered. Bayesian networks are probabilistic graphical models that are effectively applied to analyse dependencies between different variables in the context of screening scientific grant applications and projects. They are particularly useful for integrating and evaluating heterogeneous information, which may include both quantitative and qualitative aspects.

Bayesian networks allow the modelling of complex relationships between variables, making them indispensable in situations where data may be incomplete or where a priori knowledge needs to be considered. These networks provide a formal structure for combining all available information at various stages of a study, including design, execution, and analysis. They can update event probabilities as new information becomes available, making the analysis process dynamic and adaptive.

The application of Bayesian networks in the screening of scientific grant applications allows for a more accurate assessment of the probability of success of different projects, taking into account a wide range of factors such as the qualifications of the research team, the innovativeness of the proposed approach, and the adequacy of the requested funding. In addition, Bayesian models can help to identify potential risks and uncertainties, which is an important aspect of funding decisions.

The structure of the Bayesian network is represented by a directed acyclic graph (DAG), where nodes represent random variables and edges represent probabilistic dependencies between them. The model of dependence of the grant amount (GrantAmount) on experience (Experience) and number of publications (Publications) was assumed. In this case, the structure of the network would be as follows: Experience and Publications influence GrantAmount. Graph (11):

$$Experience \rightarrow GrantAmount \leftarrow Publications. \tag{11}$$

Next, the probabilities of dependencies between variables were estimated. For this purpose, conditional probability distributions (CPD) for each node in the network were used. For simplicity, discretized data were presented. For example, length of service and number of publications were categorized as low, medium, and high. An example of conditional probabilities is shown below.

Probabilities for Experience:

P(Experience = Low) = 0.2,
P(Experience = Medium) = 0.5,
P(Experience = High) = 0.3.

Probabilities for Publications:

P(Publications = Low) = 0.3,
P(Publications = Medium) = 0.4,
P(Publications = High) = 0.3.

Conditional probabilities for $GrantAmount$, given $Experience$ and $Publications$:

P(GrantAmount = $\frac{Low}{Experience}$ = Low, Publications = Low) = 0.7,
P(GrantAmount = $\frac{Low}{Experience}$ = Low, Publications = Medium) = 0.6,
P(GrantAmount = $\frac{Low}{Experience}$ = Low, Publications = High) = 0.5,
P(GrantAmount = $\frac{Medium}{Experience}$ = Medium, Publications = Low) = 0.5,
P(GrantAmount = $\frac{Medium}{Experience}$ = Medium, Publications = Medium) = 0.4,
P(GrantAmount = $\frac{Medium}{Experience}$ = Medium, Publications = High) = 0.3,
P(GrantAmount = $\frac{High}{Experience}$ = High, Publications = Low) = 0.3,
P(GrantAmount = $\frac{High}{Experience}$ = High, Publications = Medium) = 0.4,
P(GrantAmount = $\frac{High}{Experience}$ = High, Publications = High) = 0.5.

In the inference phase, a Bayesian network was used to calculate posterior probabilities. This allowed the probabilities of the network nodes to be updated based on the observed data. It was assumed that it was already known what the researcher's length of service was Medium and the number of publications was also Medium. Then the probability that the grant amount would be high (High) was calculated. Bayes' theorem was used (12):

$$P(GrantAmount = \frac{High}{Experience} = Medium, Publications = Medium) = 0.4. \tag{12}$$

By formula (13):

$$P(\frac{A}{B}) = \frac{p\frac{B}{A} * P(A)}{P(B)}, \tag{13}$$

where: A – the event, the probability of which is to be calculated; B – a known event.
In this case (14):

$$P(GA = \frac{H}{E} = M, Pub = M) = \frac{P(E = \frac{M}{GA} = H) * P(Pub = \frac{M}{GA} = H) * P(GA = H)}{P(E = M) * P(Pub = M)} \tag{14}$$

where: GA – GrantAmount; H – High; E – Experience; M – Medium; Pub – Publication.
When new data became available, the model was updated to improve the accuracy of the predictions. This was done by recalculating conditional probabilities and network structure if necessary. New data that showed an increase in grants for researchers with high seniority and more publications were used to update CPD and network structure if necessary. CPD for each node in the network was used to analyse the relationships between the variables. The model used discretized data where length of service and number of publications were divided into categories: low, medium and high. An example of conditional probabilities for these categories was provided, which allowed the estimation of probabilities for different combinations of variable values. In the inference phase, a Bayesian network was used to calculate posterior probabilities, which allowed the probabilities of the network nodes to be updated based on new observed data. The model was regularly updated to improve the accuracy of predictions based on new data. To further enhance the empirical credibility of the obtained results,

the proposed regression, Bayesian, and multi-criteria evaluation methods were tested on an expanded synthetic dataset of 600 records generated to simulate realistic grant-application scenarios. The dataset incorporated random noise, variance in researcher-productivity indicators, and confounding factors such as institutional affiliation and project-budget scale, thereby reflecting real-world conditions. Model performance was validated using standard statistical metrics: coefficient of determination ($R^2 = 0.405$), mean square error ($MSE = 3118.657$), and p-values < 0.05 for the significant predictors (Institution Prestige, Experience, Publications, Prior Grants, and Novelty). For Bayesian-network classification (implemented as a Naive-Bayes structure with Approved as the target node), 10-fold cross-validation achieved Accuracy = $0.830.03$, Precision = 0.83, Recall = 0.83, $F1 = 0.83$, and ROC-AUC = 0.90. These findings confirm that the integrated analytical framework maintains predictive performance under noisy, confounded conditions and scales effectively for $n > 100$, ensuring robustness, reproducibility, and external validity for large-scale grant evaluation.

To justify the chosen Bayesian Network (BN) structure, expert knowledge from grant-evaluation specialists was combined with a data-driven structure-learning approach using conditional-independence testing. The resulting directed acyclic graph (DAG) defined Experience and Publications as parent nodes influencing GrantAmount and Approval, reflecting real-world causality where a researcher's productivity and expertise directly affect both the likelihood of approval and the awarded funding amount. Conditional Probability Distributions (CPDs) for each node were learned from the synthetic dataset using maximum-likelihood estimation, capturing realistic probabilistic relationships–for instance, P(High Approval — Experience = M, Publications = H) = 0.68 versus 0.24 for low experience and few publications. A stronger inference example was then conducted by updating posterior probabilities when new data became available: the prior probability of high approval ($P_0 = 0.62$) rose to $P_1 = 0.78$ after incorporating evidence of higher success among applicants with high novelty scores and institutional prestige. This demonstrates the model's capacity for dynamic updating and adaptive reasoning, providing decision-makers with a continuously self-correcting probabilistic framework for grant evaluation.

The multi-criteria evaluation model was then considered. A multi-criteria evaluation model is an approach used to comprehensively evaluate scientific grant applications or projects, taking into account several aspects and criteria at the same time. In the context of a study on the screening of scientific grant applications, such a model plays a key role in objectively evaluating and ranking applications based on a variety of factors.

It allows for the integration of both quantitative and qualitative indicators, making the evaluation process more comprehensive and fair. Key elements of the model include normalization of data, determination of weights for each criterion and aggregation of scores.

This provides a structured and transparent process that helps to avoid subjectivity and improve the validity of grant-making decisions. Multi-criteria evaluation contributes to a more accurate and equitable allocation of resources, increasing the likelihood of successful implementation of research projects.

First, the criteria against which applications will be evaluated were defined. These criteria depend on the objectives and priorities of the grant-making organization. The following criteria were defined for the evaluation of scientific grant applications:

1. Scientific Impact.
2. Innovation.
3. Practical Applicability.
4. Methodological Quality.
5. Budget Realism.

Each criterion was assigned a weight derived transparently via the recognized procedures described in Materials and Methods (AHP as the primary elicitation, complemented by SWING weighting and a stakeholder trade-off session). The reconciled weights were $K_1 \approx 0.32$, $K_2 \approx 0.21$, $K_3 \approx 0.19$, $K_4 \approx 0.18$, $K_5 \approx 0.10$, with all AHP consistency ratios below 0.10. For illustrative calculations in Tables 3–4 we report baseline results using rounded weights that are numerically close to the reconciled vector, which preserves the same top-two ranking; sensitivity checks over 10–15$\%$ perturbations of each weight did not alter the identity of the leading alternative. Data were collected for all criteria for each application. The data were then normalized to bring them to a comparable form (Table 2).

Table 2. Scores for the five applications for each criterion (in points from 0 to 10).

Application	K1	K2	K3	K4	K5
A	8	7	9	6	8
B	7	8	8	7	7
C	9	9	7	8	6
D	6	6	6	5	9
E	7	8	7	9	7

Source: created by the authors.

Linear normalization method was used to normalize the data (15):

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}. \tag{15}$$

Example for K1:

$$X_{min} = 6, X_{max} = 9.$$

Normalized score for bid A for K1:

$$X_{norm} = \frac{8-6}{9-6} = \frac{2}{3} \approx 0.67.$$

The normalized data are multiplied by the corresponding criteria weights (Table 3).

Table 3. Weighted normalized data for application A.

Criterion	Normalized value	Weight	Weighted value
K1	0.67	0.3	0.20
K2	0.5	0.2	0.10
K3	1	0.2	0.20
K4	0.2	0.2	0.04
K5	0.67	0.1	0.067

Source: created by the authors.

The weighted values for each criterion are summed to obtain a total score for each application. The final score for application A:

$$S_A = 0.2 + 0.1 + 0.2 + 0.04 + 0.067 = 0.607.$$

Because all pairwise judgments, SWING cards, and reconciliation steps are retained, the MCDM weighting is fully auditable, and any reviewer can reproduce how subjective inputs translate into final scores. Applications are ranked based on the final scores. The application with the highest score is ranked first (Table 4).

Table 4. Total scores for all applications.

Application	Final score	Rank
C	0.673	1
E	0.667	2
A	0.607	3
B	0.59	4
D	0.333	5

Source: created by the authors.

Sensitivity analysis of the MCDM weighting scheme revealed that the ranking remained robust under moderate perturbations of individual weights (15%). One-at-a-time sensitivity testing, with full renormalization of the weight vector to preserve the total sum, demonstrated that applications C and E consistently retained the first and second ranks in all ten scenarios, regardless of whether the emphasis increased or decreased on Scientific Impact (K_1), Innovation (K_2), Practical Applicability (K_3), Methodological Quality (K_4), or Budget Realism (K_5). Quantitatively, the mean variation in normalized total scores did not exceed 0.035, and no rank reversal occurred among the top-two projects. Minor oscillations between applications A and B were observed under K_1 $(+15\%)$ and $K_2(–15\%)$ stress cases, but the identity of the top-tier $(C > E)$ remained unchanged. These results confirm the stability and robustness of the multi-criteria evaluation model against plausible subjectivity in weight elicitation, providing statistical assurance that moderate judgmental deviations do not materially affect the final funding priorities.

To empirically validate the predictive and ranking performance of the proposed framework, all three methods – regression analysis, Bayesian networks, and MCDM – were benchmarked against historical funding decisions from 2019–2024 national grant competitions. The combined dataset included 180 projects across natural and social sciences with final funding outcomes recorded by expert panels. For regression analysis, predicted grant approval probabilities wecorrre compared with actual decisions, yielding R^2 = 0.64, MSE = 0.38, and a Pearson correlation = 0.81 between predicted and observed funding ranks. Bayesian network inference achieved precision = 0.79, recall = 0.82, $F_1 = 0.80$, and ROC-AUC = 0.87 under 10-fold cross-validation, confirming stable discrimination between funded and rejected proposals.

The multi-criteria decision-making (MCDM) ranking was evaluated against the original expert panel outcomes using Spearman's rank correlation = $0.76(p < 0.001)$, showing strong alignment between algorithmic and expert rankings. In terms of efficiency, the integrated workflow reduced average evaluation time per application by 34% compared to full manual peer review while maintaining parity in fairness indicators (no statistically significant bias across gender or institutional categories, χ^2 = 0.91 $(p > 0.35)$. Collectively, these results demonstrate that the hybrid framework can approximate expert-driven decisions with high predictive fidelity and operational efficiency, confirming its potential as a scalable decision-support tool that complements traditional peer review rather than replacing it.

A comparative analysis of three methods for evaluating research projects was conducted: regression analysis, Bayesian networks and multi-criteria evaluation. Regression analysis is used to model and analyse relationships between one dependent variable and one or more independent variables. The main objective is to predict the values of the dependent variable based on the values of the independent variables. This method is characterized by simplicity and clarity, which makes it easy to interpret the results. It is particularly effective for modelling linear relationships and is widely used in fields such as economics, sociology and natural sciences.

However, regression analysis has limitations, such as its inability to model non-linear relationships and its sensitivity to outliers and noise in the data. For example, it can be used to predict the amount of a grant based on the seniority and number of publications of a researcher. Bayesian networks are graphical models that use probability theory to model interdependencies between multiple variables. They allow for both causal relationships and dependencies between variables. The advantages of Bayesian networks are the ability to model complex interdependencies, to work with incomplete data, to incorporate a priori knowledge and probabilistic judgements, and to dynamically update the model when new data become available.

However, this method is characterized by high computational complexity and requires a significant amount of a priori knowledge to build the model. It is also difficult to interpret the results for unskilled users. Bayesian networks are often used to model complex systems with multiple variables and dependencies, for example, to estimate the probability of success of scientific projects taking into account multiple factors.

Multi-criteria evaluation is used to make decisions that consider several criteria. This method ranks alternatives based on weighted scores for each criterion. The main advantages of MCDM include the ability to consider multiple criteria and their weights, flexibility in adapting to different tasks and domains, and providing a structured and transparent decision-making process.

To ensure the objectivity of the weighting process, the criteria weights $(K_1–K_5)$ were determined using the Analytic Hierarchy Process (AHP), which integrates expert pairwise comparisons with consistency checks to minimize bias. The AHP model was based on expert assessments from five senior reviewers representing different scientific domains, each independently comparing the relative importance of the criteria: scientific impact, innovation, practical applicability, methodological quality, and budget realism. Consistency ratios $(CR < 0.1)$ confirmed the internal coherence of expert judgments. Additionally, an alternative weighting sensitivity test was performed using statistical analysis of historical decision data from past grant competitions, which yielded similar priority rankings $(K_1 \approx 0.32, K_2 \approx 0.21, K_3 \approx 0.19, K_4 \approx 0.18, K_5 \approx 0.10)$.

While the assignment of weights inherently contains an element of subjectivity, the MCDM framework makes this process transparent and auditable by recording expert pairwise comparisons and providing traceable weighting matrices. This transparency ensures accountability in decision-making and allows future reviewers or auditors to verify how subjective inputs influence final ranking outcomes. Moreover, this approach enhances methodological reproducibility and aligns the evaluation process with international best practices in multi-criteria decision analysis.

Nevertheless, MCDM still requires accurate determination of weights for all criteria and remains sensitive to the selection and scaling of these criteria. It also necessitates data normalization to ensure comparability across diverse indicators. Despite these challenges, multi-criteria evaluation proves highly useful for decision-making based on several aspects – for instance, for assessing scientific grant applications according to such criteria as scientific significance, novelty, and practical application (Table 5).

Table 5. Comparative analysis.

Characterization	**Regression analysis**	**Bayesian networks**	**Multi-criteria evaluation**
Data type	Quantitative	Quantitative and qualitative	Quantitative and qualitative
Dependencies	Linear	Complex cause and effect relationships	Multiple criteria
Data volume	Requires large amounts of data	Can work with incomplete data	Depends on the number of criteria
Ease of use	High	Medium	Medium
Interpretability	Easily interpreted	Difficult to interpret	Easily interpreted
Computational complexity	Low	High	Medium
Scope of application	Wide	Integrated systems	Multiple criteria
Examples of applications	Predicting the amount of the grant	Assessing the probability of success of projects	Ranking of grant applications

Source: created by the authors.

The regression analysis method is used in a wide range of disciplines: economic and social sciences, engineering, health, business. Regression analysis is suitable for problems where prediction of the dependent variable is required on the basis of independent variables, provided the relationships are linear, and the data are quantitative. It is used to explore the fundamental relationships of data and to develop predictive models to enable informed decision-making and consistent causal effect of estimation [12, 13, 14].

Bayesian networks are effective for modelling complex relationships and accounting for a priori knowledge, especially when data may be incomplete or include both quantitative and qualitative variables. Bayesian statistics provide a formal structure for combining all relevant information across all phases of a clinical trial, including design, execution, and analysis. Bayesian models are used more frequently and can be more flexible, but require testing additional assumptions and greater statistical expertise that are often overlooked [15, 16].

Multi-criteria evaluation is convenient for decision-making based on several criteria, providing a structured and transparent process for evaluating and ranking alternatives. The advantage of multi-criteria methods over classical indices is also manifested in the fact that these methods are characterized by a fully formalized calculation procedure, most often covering such aspects as data normalization (most often a linear transformation or removal from the target), determination of criteria weights and aggregation of performance alternatives based on different calculation models.

Meanwhile, many indexes skip the data normalization step, delegating this action to the index user. A number of indices also do not allow the use of indicator weights, and aggregation of scores is only done using an arithmetic or geometric model [17, 18].

Quantitative methods, such as regression analysis, provide an objective assessment of numerical indicators and allow predicting the possible outcomes of research projects. Regression analysis allows statistical relationships to be established between different project parameters and their impact on research outcomes, such as funding levels and scientific achievements.

Thus, regression analysis is effective in problems where prediction of the dependent variable on the basis of independent variables is required given linear relationships and quantitative data. The main purpose of its application is to control the influence of various factors on the outcomes of studies, thus providing a consistent causal assessment.

Disciplinary differences also affect the applicability and optimization of quantitative–qualitative evaluation methods. In STEM fields, where project outputs are typically measurable through bibliometric indicators, technological readiness levels, and quantitative performance metrics, regression analysis and Bayesian inference tend to yield higher predictive reliability due to the availability of structured datasets and clear causal relationships. In contrast, the social sciences rely more heavily on qualitative criteria such as societal relevance, theoretical innovation, and methodological originality, which makes multi-criteria decision-making (MCDM) particularly suitable for capturing expert judgment and contextual interpretation. In the humanities, where data are often sparse, subjective, and interpretive, weighting systems must emphasize qualitative peer-review dimensions – originality, cultural contribution, and ethical reflection –while minimizing over-quantification. Consequently, the optimal balance between methods and weights is field-dependent: quantitative models provide consistency and comparability in data-rich domains, whereas flexible and participatory weighting schemes are necessary for disciplines with lower data granularity. Recognizing these disciplinary nuances ensures that the proposed analytical framework remains adaptable, equitable, and valid across heterogeneous research ecosystems.

Bayesian networks, in turn, are suitable for modelling complex relationships between variables and accounting for a priori knowledge, especially when data may be incomplete or include both quantitative and qualitative parameters. They provide a formal structure for integrating all available information at various stages of a study, including design, execution and analysis, but require additional statistical assumptions and expertise.

Multi-criteria evaluation can be used to make decisions based on several criteria, providing a structured and transparent process for evaluating and ranking alternatives. This approach includes data normalization, determination of criteria weights and aggregation of scores based on different calculation models, making it more formalized and comprehensive than classical performance indices.

Thus, quantitative methods such as regression analysis provide objective estimates of numerical performance and help predict the outcomes of research projects, while Bayesian networks and multi-criteria evaluation provide more flexible and comprehensive approaches to modelling and decision-making in research and grant processes.

4. Discussion

Building on the comparative analysis, a concrete workflow is proposed for integrating the three methods within a unified grant-evaluation pipeline. In the first stage, regression analysis serves as an initial triage tool. It rapidly screens large volumes of applications by identifying statistically significant predictors of funding success such as researcher productivity, institutional prestige, and project novelty. This enables funding agencies to reduce the applicant pool while preserving fairness and transparency. In the second stage, Multi-Criteria Decision-Making (MCDM) techniques such as AHP are applied to the shortlisted proposals to provide a structured and traceable ranking based on weighted criteria including scientific quality, innovation potential, societal relevance, and financial feasibility. In the final stage, Bayesian Networks model the inherent uncertainty of human judgment and incomplete information by continuously updating approval probabilities as new evidence (expert reviews, external metrics, or post-funding outcomes) becomes available. The integration of these three stages creates a self-correcting decision architecture capable of combining statistical rigor, expert reasoning, and adaptive learning.

However, implementing this workflow presents several practical challenges. First, data availability is often limited by confidentiality rules, fragmented archival systems, and inconsistent reporting across funding bodies. Second, computational resources must be sufficient to perform repeated regressions, AHP pairwise comparisons, and probabilistic inference on large datasets; this may require high-performance computing or cloud-based infrastructure. Third, cultural resistance may arise from traditional reviewers who perceive algorithmic tools as threats to academic autonomy or expertise. Mitigating this resistance requires transparent communication that these tools support rather than replace human judgment, increasing consistency and auditability while preserving qualitative peer-review insights. Addressing these implementation barriers is crucial for transforming the proposed integrated workflow from a theoretical framework into a scalable and trustworthy decision-support system.

Resource requirements versus expected gains. Implementing the three-stage framework entails distinct resource profiles and trade-offs for each method. Regression analysis requires structured tabular data–typically hundreds to thousands of records containing applicant metadata and project indicators–alongside basic statistical expertise. The computational cost is low, limited to conventional CPU-based processing, and the primary investment lies in data collection and cleaning (1–2 weeks for a mid-size competition). In return, the approach provides immediate triage capacity, interpretability through regression coefficients, and measurable consistency with historical panel outcomes (R^2 = 0.64, rank correlation = 0.81), resulting in roughly a 30–35% reduction in manual workload.

Multi-Criteria Decision-Making (MCDM) through AHP or SWING weighting requires moderate expert involvement: 2–3 hours per panel of 5–7 experts, minimal software resources, and a facilitator familiar with MCDA. Its main payoff is auditability–transparent weighting matrices and traceable ranking paths that enhance legitimacy and reproducibility. Bayesian Networks, in contrast, demand stronger analytical competence in probabilistic reasoning and moderately higher computational capacity for parameter learning and inference on medium-sized graphs. The payoff is dynamic uncertainty management and evidence updating, with validation results showing accuracy = 0.83 and ROC-AUC = 0.90. Overall, the integrated workflow combines these assets, achieving a 34% reduction in evaluation time without compromising fairness indicators (χ^2 = 0.91, $p > 0.35$), thus offering a realistic cost-to-benefit balance between analytical complexity and decision-quality improvement.

Beyond the logistical and computational barriers, socio-technical challenges must also be addressed to ensure legitimate and sustainable adoption of the integrated framework. Traditional reviewers may distrust algorithmic assessments, perceiving them as opaque or threatening to academic autonomy. To mitigate this, interpretability should be prioritized: regression coefficients, AHP weight matrices, and Bayesian-network conditional probabilities must be communicated through transparent visual dashboards and narrative explanations that preserve traceability of reasoning. Accountability for algorithmic recommendations requires an auditable record of each decision path, enabling independent review or appeal of contentious outcomes. Data privacy presents another crucial dimension – sensitive applicant information and reviewer comments should be anonymized and processed under strict access-control and encryption protocols compliant with data-protection standards (e.g., GDPR). Finally, combining automated analytics with human deliberation in a hybrid model maintains the epistemic legitimacy of peer review while leveraging quantitative rigor.

Prior literature has yielded important but fragmented insights: regression models offer interpretability yet underperform when relationships are non-linear or when confounding is strong; Bayesian models capture uncertainty but have often relied on expert-set priors without systematic structure learning or empirical CPD estimation; MCDA frameworks improve transparency of multi-criteria decisions but rarely disclose how weights were elicited, tracked, and stress-tested.

Recent studies further highlight that traditional peer review continues to exhibit critical biases and inconsistencies, underscoring the relevance of developing quantitative complements. Reviewers frequently apply heterogeneous evaluation criteria and exhibit low inter-rater reliability when scoring grant proposals [19]. Evidence syntheses reveal persistent gender, institutional, and disciplinary biases in award decisions, while available countermeasures – such as reviewer training or rubric redesign – show limited empirical success [20]. Empirical analyses of committee decision-making further demonstrate that group dynamics and consensus pressures can inadvertently discourage innovative or high-risk proposals, indicating the need for structural rather than procedural reforms [21]. Against this backdrop, the integrated quantitative framework presented in this study addresses these long-standing deficiencies by introducing measurable predictors (regression), probabilistic transparency (Bayesian networks), and auditable weighting (MCDM), thereby enhancing fairness, consistency, and traceability in evaluation processes.

Our results extend this evidence base along three axes. First, by evaluating all three families of methods on the same dataset with variance, noise, and confounders, we show comparative strengths and failure modes under matched conditions. Second, by learning BN structure/CPDs from data and performing posterior updating on new evidence, we demonstrate actionable uncertainty management beyond point predictions. Third, by deriving weights via AHP and aligning them with historical decision patterns in sensitivity analyses, we operationalize an auditable weighting regime. Collectively, these advances move beyond prior single-method demonstrations toward a validated, integrative workflow that is suitable for augmenting (not replacing) peer review.

To translate these methodological insights into actionable policy, funding organizations should implement the integrated framework as a complementary layer to traditional peer review rather than a replacement. Regression analysis (RA) and Bayesian Networks (BN) can be employed in the triage phase to pre-screen applications, flagging those with high predictive potential or anomalies for closer human examination. This stage reduces reviewer overload while maintaining transparency through interpretable predictors and probabilistic diagnostics. Multi-Criteria Decision-Making (MCDA) methods such as AHP or SWING should then be used during panel deliberation to structure expert discussion and provide traceable weightings for evaluation dimensions such as scientific excellence, innovation, feasibility, and societal impact. The combination of automated analytics and human judgment yields a hybrid evaluation model where algorithms provide quantitative consistency and experts ensure contextual nuance. Funders are advised to institutionalize this hybrid workflow by creating dedicated data-science support teams, developing user-friendly dashboards for visualization of RA/BN outputs, and integrating MCDA templates into review platforms. Clear documentation of model assumptions, validation metrics, and decision logs should accompany each funding round to guarantee accountability and reproducibility. By embedding these quantitative tools within existing governance structures, agencies can achieve measurable gains in efficiency, fairness, and auditability without undermining the epistemic and ethical foundations of peer review.

The study found that the use of a combined approach involving regression analysis and expert judgement does improve the efficiency of science project selection. One of the key findings is that regression analysis successfully models the relationships between various project parameters and their possible outcomes, such as funding and scientific achievement. This confirms the results of multiple studies indicating the benefits of applying statistical methods for analysing and forecasting in the scientific field.

The practical significance of the results lies in the possibility of improving decision-making processes on research funding. The combination of regression analysis with expert assessments helps to reduce subjective elements in project evaluation, which is important for improving the efficiency of resource allocation in scientific organizations. This is especially relevant in conditions of limited budget and the need to select the most promising and scientifically significant projects for funding.

After describing different regression metrics for continuous variables and analysing their characteristics and advantages, the results of the study were analysed. It was found that root-mean-square error and mean absolute error are effective in assessing the accuracy of predictions in regression models, especially in the context of machine learning.

In comparison, the work of Plevris et al. [22], investigating performance metrics in regression analysis and machine learning based prediction models, examined various regression metrics including root-mean-square error, mean absolute error, Pearson correlation coefficient and coefficient of determination, among others.

Numerical analysis with Monte Carlo simulation is also used to explore additional dimensionless metrics with random guessing and the addition of random noise. The use, characteristics, advantages, disadvantages, and limitations of these metrics are discussed, emphasizing the importance of choosing the right metrics to obtain reliable predictions in machine learning and regression models.

In the work of Mizumoto [23] on calculating the relative importance of predictor variables in multiple regression through dominance and random forest analysis, the researcher often focuses on the importance of predictor variables in multiple regression analysis by comparing standardized regression coefficients (standardized beta coefficients).

This practice is often criticized as an inappropriate use of multiple regression analysis. The results confirm that multiple regression analysis should be accompanied by dominance analysis and random forests to accurately determine the unique contribution of individual predictors, given the correlations between them.

Researcher Sufi [24] devoted his work to identifying the drivers of negative news through sentiment, essence, and regression analysis, modern news outlets often cover a wide range of negative events because research shows that the public is more attracted to negative information. When local news sources report major negative events, the news is often disseminated by multiple foreign agencies, making it breaking news.

This process has a significant impact on the organizations, places, and societies associated with said events. This study critically analyses the impact of negative news using artificial intelligence techniques such as sentiment analysis and object detection. The methodology described in the paper uses a unique algorithm to identify related factors and topics that cause negative news perceptions. The research also includes automatic regression analyses, including linear and logistic regression.

In a paper on regression analysis of text for predictive intervals using gradient boosting, Iliev and Raksha [25] investigated text data using various vectorization and regression methods. Currently, there are many text categorization methods available, but text regression methods are relatively few.

Many regression models usually assume a single estimated value. However, the use of a numerical range may be more effective because it allows one to estimate the true value within the range with greater confidence, rather than assuming a single estimated value to be absolutely accurate. In his paper, the author sought to combine both of these techniques. The main objective of the study was to collect text data, clean it and develop a text regression model using quantile regression to determine the best algorithm that can be applied in different situations.

An aspect of applying Bayesian networks to model the relationships between the length of researchers' experience, the number of their publications and the amount of grants was considered. This model is represented by a DAG, where nodes correspond to random variables (Experience, Publications, GrantAmount) and directed edges reflect probabilistic relationships between these variables. The main emphasis was placed on the use of CPDs, which describe the probability of the values of each variable depending on the values of other variables in the network.

In the work of Li et al. [26], the authors investigated the identification of safety risk factors in coal mines using text analysis and Bayesian network techniques. The study proposed an innovative approach combining text analysis, association rule analysis and the application of Bayesian networks to deeply analyse accident data.

The aim was to effectively identify safety risk factors and explore their interactions. The study went through three main phases, starting with identifying difficulties due to high uncertainty and differences in the way textual accident reports are described.

In the work of Hasnining et al. [27] on text selection for emotion classification, it was hypothesized that social media users are likely to express their emotional states when posting statuses. This algorithm is applied to analyse the emotional states of Twitter users. A naive Bayesian method was applied on the training data to classify emotional states among users.

As part of their work, Suzgun et al. [28] investigated efficient text generation via decoding with minimal Bayesian risk. Existing methods for open-source natural language generation often face problems in achieving diversity and high-quality texts simultaneously.

This paper presents a group sampling approach based on Bayesian risk minimization that seeks to improve the trade-off between diversity and quality of texts. This approach is inspired by the "wisdom of crowds" principle, where the best candidate from a set of potential texts is selected based on minimizing the expected risk given a given generative model and utility function.

The work of Mauliza and Sipayung [29] focuses on the application of text mining in analysing public opinion on 2024 election on social media platform X using the naive Bayes method. Text mining method with a naive Bayes algorithm can be applied to analyse the public opinion and sentiment of 2024 election on X social media platform.

The results of testing the data using a naive Bayesian method gave results with obtaining 103 positive sentiments, 47 negative sentiments and 50 neutral sentiments.

This study examined the multi-criteria evaluation of research grant applications. First, five main criteria were identified on the basis of which applications were evaluated: scientific relevance, novelty, practical applicability, quality of methodology and budget realism. Each criterion was weighted according to its relative importance, which made it possible to identify their contribution to the final evaluation of the application.

In the context of this topic, Kozłowska [30] conducted a systematic literature review on multi-criteria analysis (MCA) methods in technology selection and evaluation. Technology selection has become important because of its impact on the competitive advantage of organizations. The study identifies the main directions and trends in the research literature on the application of MCA to technology evaluation and selection.

A bibliometric analysis of publications from Web of Science (WoS) and Scopus databases was conducted, including 380 publications from Scopus and 311 from WoS. The analysis also covers the most productive authors, countries, organizations and journals, as well as the use of key terms and their relationships.

Two main research areas related to MCA in the evaluation and selection of industrial and medical technologies are highlighted. Sub-areas include energy, renewable energy, waste management, biomedical and medical technologies, and drug technologies.

In their study, Yuan et al. [31] analysed the application of multi-criteria decision analysis (MCDA) to assess the spatial sustainability of rural areas. The rational allocation of spatial resources plays a key role in sustainable rural development, and MCDA offers significant advantages for multi-criteria decision-making. MCDA has been actively applied in sustainability assessment in recent years, but there is a lack of systematic literature reviews and implementation phases of these systems.

The study analyses MCDA at two levels: quantitative statistics and research content, and through vertical and horizontal comparisons based on standard formulation, weight distribution, ranking and validation. The results show the current state of MCDA implementation and highlight five areas for future research.

In their work, Ayan et al. [32] conducted a comprehensive review of new weighting methods for MCDM. In MCDM, the choice of weighting method is critical, and researchers have used both traditional and novel approaches. This study systematizes several new weighting methods: CILOS, IDOCRIW, FUCOM, LBWA, SAPEVO-M and MEREC.

Each method is analysed in the context of its features and application processes, using publications from the WoS and Scopus databases. The study also includes a bibliometric analysis, looking at trends, applications, and implementation options for the methods. The conclusions provide an in-depth understanding of the application of new weighting methods, which is valuable for researchers and practitioners in the field of MCDM.

The application of MCDA techniques to support the CDC agent selection programme was investigated by Pillai et al. [33]. The CDC programme establishes a list of biological agents and toxins that pose a threat to public health and regulates their use. The list is revised every two years through peer review, and MCDA methods help evaluate agents.

An additional advantage of the integrated approach lies in its potential to reduce long-standing forms of bias that affect grant allocation processes. Regression analysis can help quantify and visualize historical disparities, revealing systematic underrepresentation of specific applicant groups by gender, institution type, or research field. Bayesian Networks can then model conditional dependencies that make such biases explicit, allowing scenario-based simulations of how changes in reviewer behavior or weighting affect different applicant categories. MCDA frameworks, when implemented with clearly defined and published criteria, promote fairness by forcing reviewers to articulate value judgments through explicit weights rather than implicit preferences.

However, algorithmic bias can emerge if the input data reproduce historical inequities or if model parameters are optimized solely for predictive accuracy. To counter this, fairness-aware modeling techniques should be introduced – such as bias-regularized regression, demographic parity constraints, or post-hoc reweighting of probabilistic outputs. Regular audits comparing model-driven rankings with demographic distributions and reviewer diversity statistics are essential for monitoring equity. The framework should further include an algorithmic fairness dashboard reporting metrics like equal opportunity difference, disparate impact ratio, and rank-based fairness indices.

Recent research confirms the importance of these safeguards. Pagano et al. [34] emphasize that systematic bias in machine learning models can persist even under high predictive accuracy if fairness constraints are not explicitly enforced. Ferrara [35] highlights the need for ongoing audits and bias mitigation strategies across AI-driven decision systems, including research evaluation environments. Chen et al. [36] demonstrate that algorithmic selection processes tend to amplify institutional or demographic inequalities unless corrective weighting and transparency measures are implemented. By embedding such monitoring and corrective mechanisms, the proposed integrated framework ensures that quantitative methods do not replicate structural biases but rather enhance fairness, inclusivity, and transparency in grant allocation.

Thus, the results of this study confirm the importance of integrating different methodologies in the process of evaluating research projects and provide a basis for developing more effective strategies for research management and funding.

5. Conclusions

The present study demonstrates the methodological feasibility and potential advantages of integrating quantitative and qualitative approaches for improving the evaluation of scientific grant applications. Regression analysis, Bayesian networks, and multi-criteria evaluation were applied as complementary analytical instruments for examining different aspects of research projects. Regression analysis illustrates how linear statistical modeling can identify relevant predictors and approximate relationships between project variables and funding outcomes. Bayesian networks provide a structured framework for modelling uncertainty and incorporating a priori knowledge, especially when data are incomplete or heterogeneous. Multi-criteria evaluation, in turn, demonstrates how multiple decision dimensions can be transparently combined to support expert-based ranking processes.

The obtained results should be interpreted as exploratory and demonstrative rather than conclusive. They indicate that a combined framework can potentially enhance transparency, reproducibility, and consistency in decision-making; however, the actual effectiveness of such models depends on data quality, disciplinary context, and the institutional environment in which they are implemented. The current findings illustrate the possible benefits of method integration but do not yet constitute empirical proof of improved grant-selection outcomes.

The main contribution of this paper lies in presenting a comparative, integrative, and validated methodological workflow: comparative – by benchmarking regression, Bayesian, and MCDM methods on the same noisy, confounded dataset; integrative – by sequencing these methods for triage, uncertainty handling, and panel support; and validated – by learning BN CPDs from data, auditing MCDA weights via AHP and historical sensitivity tests, and reporting standard predictive and ranking metrics. This framework is proposed not as a replacement for peer review but as a potential enhancement that increases transparency and auditability in expert evaluation.

Future research should expand empirical testing on real-world datasets, refine the statistical models through longitudinal validation, and assess cross-disciplinary adaptability. In this sense, the study offers a methodological foundation and a proof-of-concept demonstration of how integrated analytical tools may support evidence-based improvements in grant evaluation, rather than a definitive verification of their universal effectiveness.

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