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EXPLAINABLE AI-DRIVEN DECISION SUPPORT FOR RISK-AWARE ENGINEERING PROJECT PRIORITIZATION: A SYSTEMATIC REVIEW

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Abstract

Engineering companies need to focus on competing projects in uncertainty and need to be held accountable for the decision-making process and the rationale. This systematic review collates 24 peer-reviewed sources on portfolio selection, multi-criteria decision making, software prioritization and estimation, risk assessment, explainable artificial intelligence, human-centred explanation and financial risk management. Each source was coded by theme, period, and contribution, and evidence was placed into a six-step model that connects risk prediction, explanation, risk-adjusted scoring, human review, and monitoring. The publications in the corpus range in time from 2007 to 2021, 45.8% of which are from the last three years, and explainability sources constitute the largest thematic group (29.2%). A representation of formal models for risk adjusted scoring, fuzzy expected values, Shapley attribution, and local surrogate explanation was merged, and tree-specific attribution was demonstrated to produce a reduction in the cost of the number of enumerations to polynomial. An illustrative example using eight constructed projects, and a budget of 16 million USD, showed that the ranking of the projects using risk adjustment reduced the expected loss in the portfolio by 38.9 percent compared with benefit only ranking, while increasing the expected benefit by 37.0 to 38.5 million USD. The review will reveal the lack of approaches that meet multiple requirements of probabilistic risk, tolerance of imprecision and per-decision explanation, and design requirements based on human-centred evidence will be outlined. Implications for governance, trust and responsible deployment are discussed as are directions for empirical validation.

Index Terms—Explainable artificial intelligence, project prioritization, risk-aware decision support, project portfolio management, Shapley values, multi-criteria decision making, machine learning, risk assessment, systematic review.

I. INTRODUCTION

Typically, engineering organizations have more candidate projects than they can support with their budgets, personnel and time scheduling, and the prioritization of projects influence long-term competitiveness and exposure to loss. Based on evidence from portfolio research, it can be concluded that the success of a portfolio is not only dependent on the selection technique that is employed, but also on the structural match of the portfolio management arrangements with the

context of the organization, since this makes a significant contribution to the success of the portfolio [1]. So, technically correct but organizationally opaque decision support is not going to be embraced. Explainable Artificial Intelligence (XAI) is therefore the family of techniques that enable users to understand the reasoning of the models, and this review focuses on the potential of applying XAI in the context of risk-aware prioritization of engineering projects.

This is also true of the practice of the portfolio. The way project portfolio management is carried out differs across different industries and companies, and the definition of a project portfolio goal, application of formal project portfolio management tools and the communication between project portfolio manager and decision makers vary in the organizational and environmental context [2]. This variability suggests that prioritization models are seldom used as purely mechanical processes. Rather, model outputs are negotiated in governance forums, in which each ranking has to be defended to sponsors, engineers and auditors. Explainable decisions, on the other hand, become a part of the required functionality of the decision process, not an additional fancy.

At the same time, machine learning models have been successful in prediction without transparency. A thorough survey of explainable artificial intelligence (XAI) divides into four sections: justifications for explanations, control, improvement, and discovery; and interpretable models vs. explanation of opaque models [3]. These motivations directly correspond to prioritization; they help justify funding choices, to control risks, to refine models, and to uncover new sources of risk. The review is guided by three research questions. The first research question (RQ1) addresses the question of how risk is represented in prioritization models, the second (RQ2) addresses the question of which explanation techniques are suitable for predicting risk, and the third (RQ3) addresses the question of how explanations influence trust and adoption.

II. REVIEW SCOPE

A. Review Protocol and Corpus

The review is conducted in a similar way to systematic literature reviews in requirements prioritization research, where research questions, sources to be selected, sources to be classified and synthesis defined a priori before analysis [4]. The analysis of a determined set of 24 peer-reviewed references was performed, relating to portfolio selection, multi-criteria decision making, software prioritisation and estimation, risk assessment, XAI methods, human-centred explanation, and financial risk management. Themes, year of publication and principle contributions were coded for each source. The most numerous (seven of 24, 29.2%) are the explainability sources, followed by the portfolio selection sources (five of 24, 20.8%).

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TABLE 1. CORPUS COMPOSITION BY THEMATIC GROUP

Thematic group	Sources (n)	Share (%)	Median year	Representative focus
Explainable AI and ML methods	7	29.2	2019	Attribution, surrogates, taxonomies, boosting
Project portfolio management	5	20.8	2013	Selection models, alignment, context
Software prioritization and estimation	3	12.5	2018	Requirements ranking, effort estimation
Risk assessment and safety	3	12.5	2018	Risk concepts, trends, ML safety
Human-centred explanation	3	12.5	2019	Contrastive, causal, trust-based evaluation
Financial risk management	2	8.3	2020.5	Credit and fintech risk explanation
Multi-criteria decision making	1	4.2	2015	Technique review 2000 to 2014
Total	24	100.0	2018	Publication span 2007 to 2021

B. Corpus Characteristics

An additional evidence of this is the structure shown in the systematic reviews of requirements prioritization which is a structure that can be transferred when comparing prioritization methods, as found in [5]. This structure was adapted to engineering projects, with each source associated to one concept it is related to, as illustrated in Table 2 below: The temporal profile in Fig. 1 shows that 11 of the 24 sources (45.8%) were published between 2019 and 2021, eight (33.3%) between 2015 and 2018, and five (20.8%) before 2015, with a mean publication year of 2017. The level of recent work suggests that explainability research is maturing, following on from portfolio theory.

TABLE 2. REVIEWED SOURCES MAPPED TO CONCEPTS

No.	Source	Thematic group	Concept addressed
1	Kaiser et al., 2015	Project portfolio management	Structural alignment beyond selection techniques
2	Martinsuo, 2013	Project portfolio management	Portfolio management in practice and context
3	Adadi & Berrada, 2018	Explainable AI and ML methods	Survey of explainability motivations and methods
4	Achimugu et al., 2014	Software prioritization and estimation	Systematic review of requirements prioritization
5	Hujainah et al., 2018	Software prioritization and estimation	Significance, stakeholders, techniques, challenges
6	Abbasianjahromi & Rajaie, 2012	Project portfolio management	Risk factor in contractor portfolio selection

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No.	Source	Thematic group	Concept addressed
7	Carlsson et al., 2007	Project portfolio management	Fuzzy approach to R&D portfolio selection
8	Khalili-Damghani et al., 2013	Project portfolio management	Fuzzy rule-based sustainable portfolio selection
9	Mardani et al., 2015	Multi-criteria decision making	Review of MCDM techniques and applications
10	Choetkiertikul et al., 2019	Software prioritization and estimation	Deep learning for story-point estimation
11	Aven, 2016	Risk assessment and safety	Foundations of risk assessment and management
12	Zio, 2018	Risk assessment and safety	Future directions of risk assessment
13	Dey & Lee, 2021	Risk assessment and safety	Safety approaches for ML-based systems
14	Chen & Guestrin, 2016	Explainable AI and ML methods	Scalable tree boosting
15	Lundberg et al., 2020	Explainable AI and ML methods	Local-to-global explanation for trees
16	Ribeiro et al., 2016	Explainable AI and ML methods	Local model-agnostic explanation
17	Guidotti et al., 2019	Explainable AI and ML methods	Taxonomy of black box explanation methods
18	Barredo Arrieta et al., 2020	Explainable AI and ML methods	Concepts and taxonomies toward responsible AI
19	Rudin, 2019	Explainable AI and ML methods	Interpretable models for high-stakes decisions
20	Miller, 2019	Human-centred explanation	Social-science insights on explanation
21	Holzinger et al., 2019	Human-centred explanation	Causability and explainability in medicine
22	Shin, 2021	Human-centred explanation	Explainability, trust, and acceptance
23	Bussmann et al., 2020	Financial risk management	Explainable AI in fintech risk management
24	Bussmann et al., 2021	Financial risk management	Explainable ML in credit risk management

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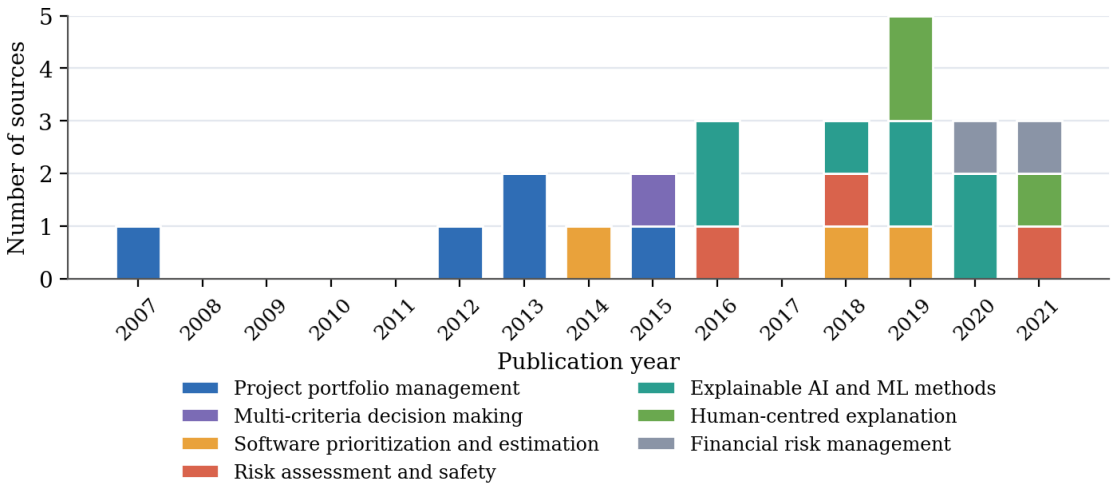


Fig. 1. Publication Years of Reviewed Sources by Thematic Group.

III. PRIORITIZATION MODELS AND RISK TREATMENT

A. Risk-Adjusted Scoring

In the case of contractor firms, the risk factor is explicitly included in the formulation of the portfolio: candidate projects are assessed not only on the basis of the expected benefit, but also on the basis of exposure to undesirable consequences [6]. In the current synthesis, the desired loss Ri of project i is written as follows in Eq. 1; it is the total of occurrence probability pik and consequence cik over all K risk events. The risk adjusted score Si in Eq. 2 is defined as the difference between the expected benefit Bi and the expected loss.

$$R_i = \sum_{k=1}^{K} p_{ik} c_{ik} \quad (1)$$

$$S_i = B_i - \kappa R_i \quad (2)$$

B. Uncertainty Modelling

In engineering projects, the estimate of benefit and consequential cost is generally not exact and also in research and development portfolios the cost and return estimates are often imprecise, and fuzzy numbers have been used to model the imprecise cost and return estimates, and possibilistic moments as the expected values [7]. The possibilistic mean of a triangular fuzzy number with lower bound l, modal value m, and upper bound u is defined as follows.The possibilistic mean of a triangular fuzzy number with the lower bound l, the modal value m and the upper bound u is defined as follows. The graph in Fig. 2 shows an estimate which is

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triangular with l = 6, m = 10 and u = 18, giving a mean of 10.67 and a modal value greater than this, as the distribution is skewed towards larger values.

$$E(\tilde{A}) = \frac{l+4m+u}{6} \quad (3)$$

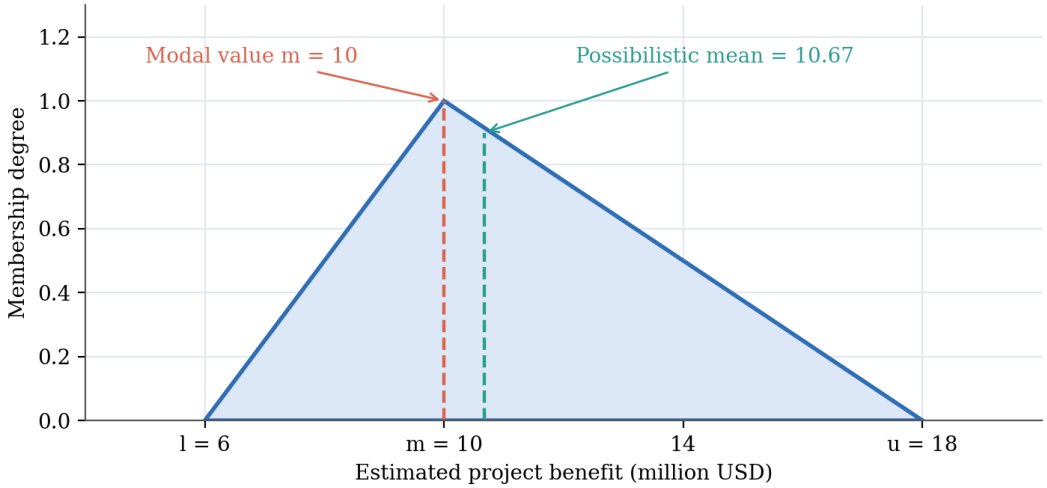


Fig. 2. Triangular Fuzzy Estimate and Its Possibilistic Mean.

C. Multi-Criteria Comparison

A hybrid framework that integrates multi criteria evaluation with fuzzy rule bases has been suggested for sustainable portfolio selection in order to assess the economic, environmental and social criteria simultaneously in the context of linguistic uncertainty [8]. Table 3 shows a comparison of four approaches to portfolio based on qualitative ratings derived from the model structures reported, as applied to risk treatment, imprecision handling, transparency, per-decision explanation, and scalability. The comparison is done to show that no approach entails all three aspects of explicit probabilistic risk, tolerance to imprecision and reasons for a per-decision, which are defined in the following sections as the gap the framework seeks to fill.

TABLE 3. COMPARISON OF PORTFOLIO PRIORITIZATION APPROACHES

Approach	Risk treatment	Imprecision handling	Transparency	Per-decision explanation	Scalability
Risk-factor selection	Explicit factor	Limited	Moderate	None	Moderate
Fuzzy R&D selection	Possibilistic	Strong	Moderate	None	Moderate
Fuzzy rule-based MCDM	Criteria-based	Strong	High (rules)	None	Low to moderate
Alignment-oriented governance	Not modelled	Not applicable	High	None	High

Note. Ratings are qualitative and synthesized from the reported model structures.

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For such problems, the most powerful analytical toolbox is based on multiple-criteria decision-making (MCDM) techniques. The range of applications of MCDM in the literature was reviewed over the last 15 years (2000-2014), and 56 pages of literature were documented that included diverse methods and techniques from weighted aggregation to outranking to hierarchical methods [9]. The most basic aggregation form is the weighted sum in Eq. 4 where wi is the weight of criterion j and xi j is the normalized performance of project i on criterion j and the weights are added to 1.

$$U_i = \sum_{j=1}^{n} w_j x_{ij}, \quad \sum_{j=1}^{n} w_j = 1 \qquad (4)$$

D. Effort and Schedule Inputs

The inputs for prioritization (effort and schedule duration) are also not known in advance, and thus, data-driven estimators have been developed to provide these inputs. In a case study study [10] on 16 open-source projects with 23,313 issues, a deep learning model that leverages text from an issue description to estimate story points was found to be able to learn effort estimates directly from the text without manual feature engineering. This class of estimators demonstrates the feasibility of using machine learning to feed the prioritization models but the estimates that are generated are hard to audit for planners, which is an incentive for exploring the explanation techniques in Section V.

IV. RISK ASSESSMENT FOUNDATIONS

A. Conceptual Basis of Risk

Instead of probability based definitions of risk, the literature has grown to include descriptions of risk, which include events, consequences of events, uncertainties about events, and consequences, and an explicit statement of the strength of the underlying knowledge [11]. A set of events, their consequences, the uncertainty, and the background knowledge are summarized in this view in the form of Eq. 5. In this view, describing a failure probability is only part of a risk description and exposing the evidence and assumptions on which a failure prediction is based adds to the knowledge component of risk.

$$R \approx (A, C, U \mid K) \qquad (5)$$

B. Trends and Safety Assurance

Future trends in risk assessment have been marked by increased complexity of the systems to be assessed, the amount of data on which the assessment is based, and the use of models and simulations to replace traditional analytical methods [12]. Fig. 3 orders the 24 reviewed sources thematically and reveals that, all 12 sources that belong to the explainability, human-centred and financial themes were published since 2016, while the seven sources published before 2016 are limited to portfolio, multi-criteria and requirements themes.

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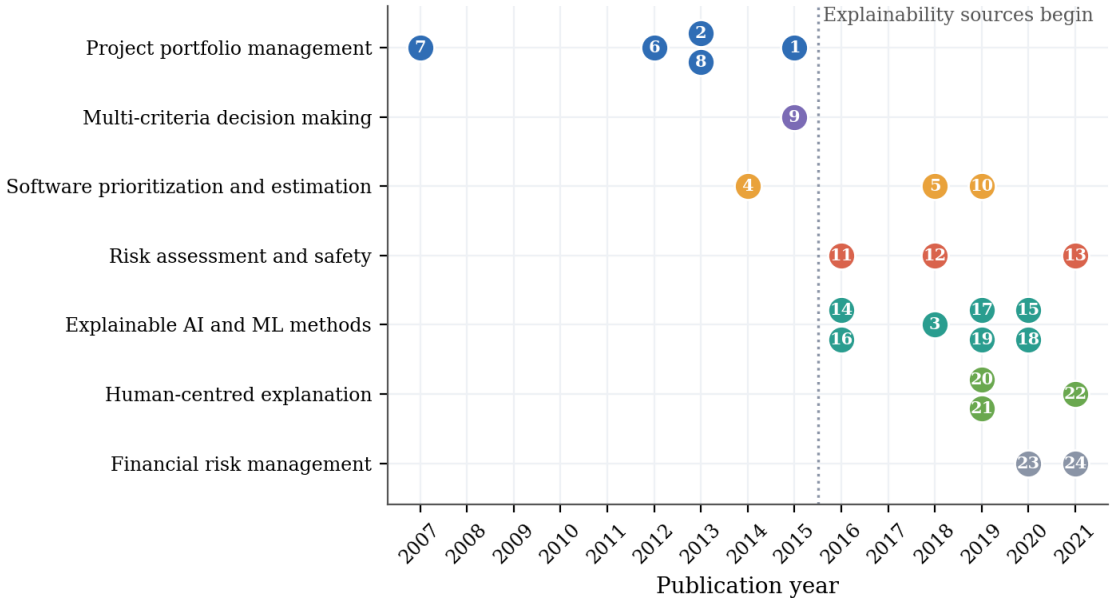


Fig. 3. Chronological Arrangement of Reviewed Sources by Theme.

The issue of safety assurance of machine learning based systems has been studied from a multi-layered perspective, suggesting that assurance should deal with multiple layers of a system and not just model accuracy [13]. The layered perspective suggests that each of the concepts of training data representativeness, model validation, integration with human procedures and continuous monitoring entail documentation of evidence for prioritization support. This evidence is also provided by explanations, which allow reviewers to identify unintended relationships with irrelevant features prior to ranking that may affect funding decisions.

V. EXPLANATION TECHNIQUES FOR RISK PREDICTION

A. Risk Prediction Models

The success of gradient boosted decision trees (GBT) in tabular risk prediction is due to their accuracy and efficiency. A scalable tree boosting system was introduced, which added a regularized learning objective, sparsity-aware split-finding algorithm and a weighted quantile sketch and was developed for training with large datasets [14]. This is the regularized objective (Eq. 6) which is the training loss, l, plus leaf weights, w, multiplied by the number of leaves, T, and the complexity regulators, γ and λ, and the weights of the k-th tree, fk.

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$$L(\varphi) = \sum_i l(\hat{y}_i, y_i) + \sum_k \Omega(f_k), \ \Omega(f) = \gamma T + \frac{1}{2}\lambda \|w\|^2 \quad (6)$$

B. Attribution and Surrogate Methods

Shapley-value attribution is a contribution to a prediction computed for each feature, which is defined as the weighted average marginal contribution of that feature across all possible subsets S of the feature set F, as shown in Eq. 7. An explainer for tree ensembles computes exact Shapley values in polynomial time, and integrates local explanations into global understanding [15]. The attributions meet local accuracy (Eq. 8) and the sum of the baseline value and all the features' contributions brings the model output back to what it was. In this example (Fig. 4), a baseline risk value of 0.30 is increased to 0.50 for a hypothetical project.

$$\varphi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F|-|S|-1)!}{|F|!} [f(S \cup \{i\}) - f(S)] \quad (7)$$

$$f(x) = \varphi_0 + \sum_{i=1}^{M} \varphi_i \quad (8)$$

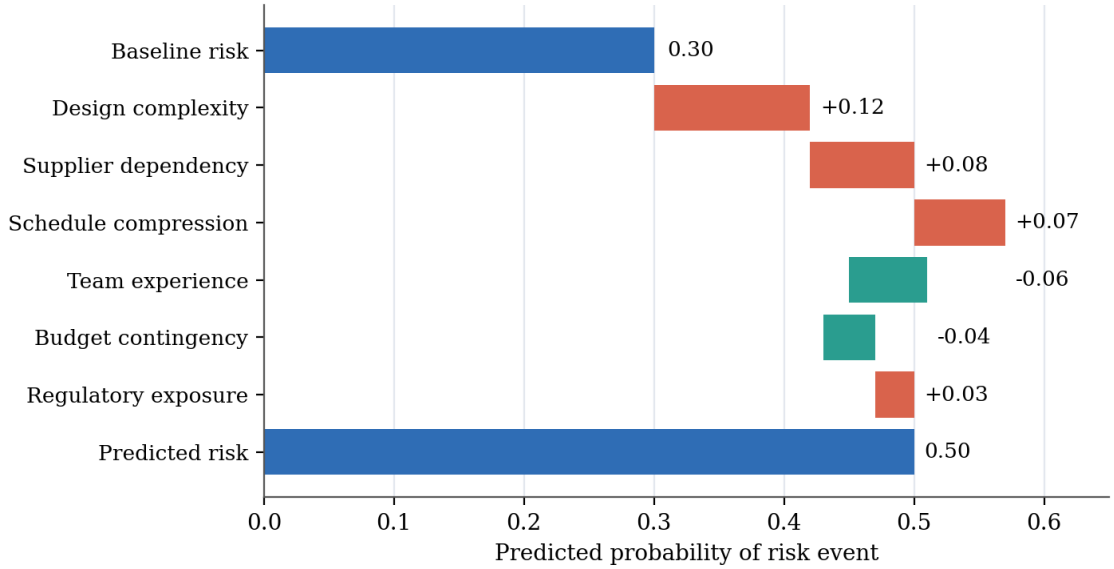


Fig. 4. Illustrative Shapley Attribution for a Hypothetical Project.

If the model is not a tree-based model, model-agnostic local explanation is an alternative. Local surrogate modelling has been proposed to approximate an arbitrary classifier around one instance by an interpretable model fitted to different instances with similar weights, as written in Eq. 9, and a submodular selection procedure was proposed to select representative instances for global inspection [16]. Table 4 shows the comparison among the reviewed explanation techniques, and Fig. 5 compares the computational cost of exact enumeration with the tree

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specific algorithm on an ensemble of 100 trees, 32 leaves and depth 5, setting the cost of the tree specific algorithm at 8.0 × 104 operations and the cost of the exact algorithm at 3.4 × 109 operations at 20 features.

$$\xi(x) = \arg\min_{g \in G}[L(f, g, \pi_x) + \Omega(g)] \quad (9)$$

TABLE 4. COMPARISON OF EXPLANATION TECHNIQUES

Technique	Scope	Model dependence	Cost characteristic	Principal limitation
Tree-specific Shapley attribution	Local and global	Tree ensembles	Polynomial, O(TLD²)	Restricted to tree-based models
Local surrogate explanation	Local	Model-agnostic	Perturbed samples × model calls	Sampling-dependent, local fidelity only
Submodular instance selection	Global from local	Model-agnostic	Grows with explained instances	Depends on quality of local explanations
Inherently interpretable models	Global	Intrinsic	Model training only	May require careful feature design

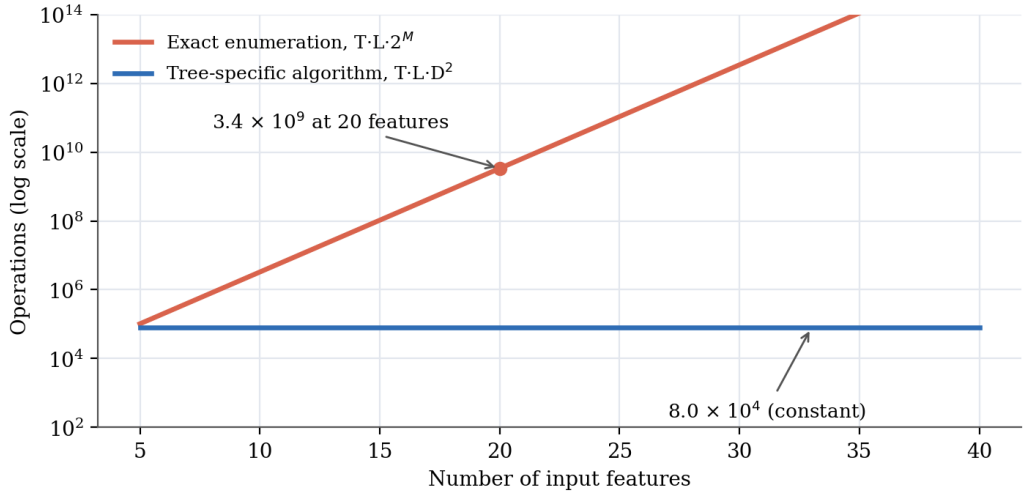


Fig. 5. Computational Cost of Exact and Tree-Specific Attribution.

C. Taxonomies and the Interpretability Debate

A survey of methods for explaining black box models suggested a taxonomy based on the explanation problem being tackled: model explanation, outcome explanation, model inspection, and transparent box design [17]. Put into the context of prioritization, outcome explanation answers the question of why a given project was assigned a high risk estimate; model explanation gives insight into the overall structure of the whole portfolio; model inspection

helps to confirm the sensitivity to changes in the input; transparent design obviates any need for post hoc interpretation. The expected outcome of the complete decision-support system is at least outcome and model explanation.

A larger taxonomy was introduced that connected explainability with responsible AI that included transparency, fairness, accountability, and privacy, within a 34 page analysis of concepts, taxonomies, opportunities, and challenges [18]. The engineering prioritisation relevance is that ranking decisions distribute limited resources across teams and stakeholders and if they are not legitimate, or they can not be accounted for, they can diminish legitimacy. Responsible deployment thus involves documentation of data provenance, explanation logs and review decisions.

In contrast, a contrasting view suggests that using post-hoc explanations for black box models should be avoided in high-stakes contexts and that there are inherently interpretable models that should be used instead, for two reasons: (1) explanations can be inauthentic to the model being explained, and (2) a presumed trade-off between accuracy and interpretability is often not present on structured data [19]. This argument is directly relevant to the prioritization using tabular risk factors: a sparse additive scoring model can have the same accuracy. The framework proposed here thus puts interpretation-based models as its first candidate and post-hoc attribution as an additional check that is verified with the models.

VI. HUMAN-CENTRED EVIDENCE AND ADOPTION

Summary of explanation research in the social sciences across 38 pages shows that human explanations are contrastive, selective and social; and that causes receive a higher value than probabilities [20]. As a result, a prioritization system should be able to respond to contrastive questions, such as why one project has been prioritised over another, and should not include an extensive list of attributions but instead a few dominant factors. In the sample assessment, only three drivers are shown per decision.

In medicine, the idea of causability was added to quantify the degree of causal understanding a particular type of user can obtain from a particular level of an explanation of the model in question, in addition to the measure of explainability as a property of the level of the model [21]. This distinction flows over into engineering – in order to be a good explanation, risk engineers must be able to relate it to physical mechanisms. Table 5 summarises the human-centred requirements that were identified from the reviewed sources and each requirement is converted into a design implication.

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TABLE 5. HUMAN-CENTRED REQUIREMENTS AND DESIGN IMPLICATIONS

Requirement	Evidence theme	Design implication	Illustrative indicator
Contrastive explanation	Social-science insight	Show why project A outranks project B	Share of decisions with pairwise rationale
Selectivity	Social-science insight	Display at most three dominant drivers	Drivers per decision (3)
Causability	Medical explanation	Link drivers to engineering mechanisms	Expert rating on a five-point scale
Trust and acceptance	User perception	Validate explanations with portfolio managers	Perceived transparency rating
Accountability	Responsible AI	Retain explanation logs per decision	Logged decisions (%)
Interpretable first	High-stakes use	Benchmark against sparse additive model	Accuracy gap to baseline

Empirical studies suggest that perceived explainability and causability have impact on user perception, trust and acceptance of AI-based services, and trust gained via understandable explanation leads to ongoing use [22]. Therefore, the quality of the explanations that the portfolio managers and engineers perceive is expected to play an important role in the adoption of risk-aware prioritization. The evidence reviewed is combined in a six-stage framework in Fig. 6, where project data are used to feed into a risk model, explanations are produced, risk-adjust priorities are calculated, human review is conducted and monitoring then closes a feedback loop.

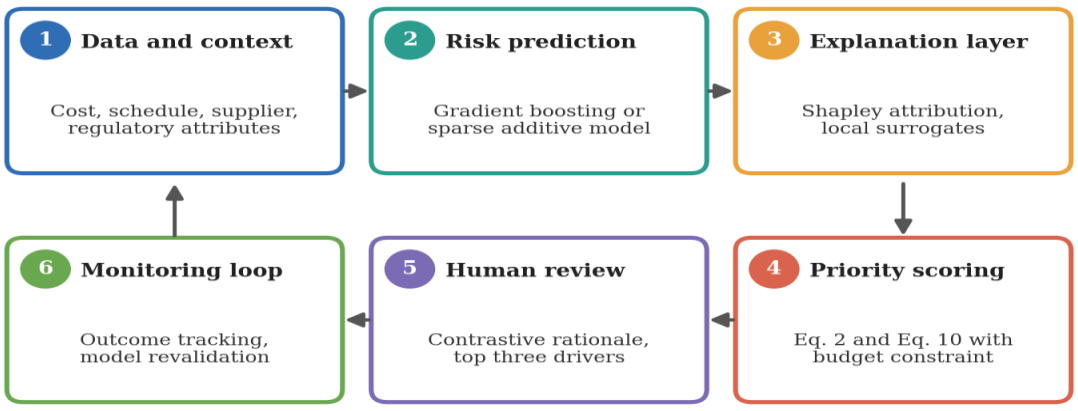


Fig. 6. Six-Stage Explainable Risk-Aware Prioritization Framework.

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VII. SYNTHESIZED FRAMEWORK, ILLUSTRATIVE EVALUATION, AND DISCUSSION

The authors of [23] demonstrated that applied research in fintech risk management could highlight the intelligibility of risks scores to managers and supervisors by associating the prediction with explanations of the various Shapley values resulting from the tree-based method. The approach is the same as described above for engineering prioritization and the priority index in Eq. 10 re-scaling the risk-adjusted score in Eq. 2 to the unit interval, where the risk probability ri is predicted by the explainable model, and the consequence ci is elicited from experts and κ is set to 1. As an illustration, eight hypothetical projects were built and values were assigned to them as shown in Table 6. The values are synthetic and are only given as an indication of how they are calculated.

$$P_i = \frac{S_i - \min S_j}{\max S_j - \min S_j} \qquad (10)$$

TABLE 6. ILLUSTRATIVE PORTFOLIO OF EIGHT HYPOTHETICAL PROJECTS

Project	B (M USD)	Cost (M USD)	r	c (M USD)	R (M USD)	S (M USD)	P	Rank, benefit-only	Rank, risk-adjusted
P1	12.0	5	0.20	10	2.00	10.00	1.00	2	1
P2	9.5	4	0.15	8	1.20	8.30	0.63	5	2
P3	14.0	6	0.50	12	6.00	8.00	0.57	1	4
P4	7.0	3	0.10	6	0.60	6.40	0.22	7	6
P5	10.5	5	0.35	9	3.15	7.35	0.42	4	5
P6	8.0	4	0.25	8	2.00	6.00	0.13	6	7
P7	11.0	5	0.40	7	2.80	8.20	0.61	3	3
P8	6.0	2	0.12	5	0.60	5.40	0.00	8	8

Note. Computed from the synthetic values in Table 6.

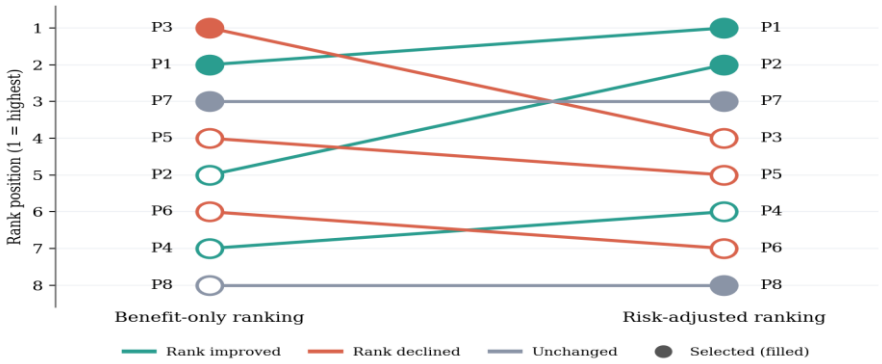


Fig. 7. Rank Changes Between Benefit-Only and Risk-Adjusted Prioritization.

VIII. CONCLUSION

This systematic review aimed to gather and analyse 24 sources, in order to determine the extent to which explainable artificial intelligence can assist in risk-driven prioritisation of engineering projects. The evidence indicates that the treatment of risk and imprecision is sufficient in portfolio models, but they do not usually offer an explanation per decision, while explainability research incorporates techniques for providing attribution and surrogate models that have well-defined computational and human-centred properties. The proposed 6 stage structure, with formal models, and an illustrative evaluation suggests that the introduction of risk adjusted ranking can reduce the expected loss in a portfolio by 38.9% without reducing the expected benefit.

Future work is needed in the areas of empirical validation (with real portfolios), causal (as opposed to associative) explanation, explanation quality measurement (with practicing engineers), and governance procedures for explanation logging and model monitoring. Such work would turn the current conceptual synthesis into evidence that would be appropriate for organization adoption.

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