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RFI-to-Field Impact Analytics for Mega-Terminal Structural Packages: A Traceability Model Linking RFIs, Revisions, and Schedule Impacts

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Rukmini Reddy Sama
Construction Management and Civil Engineering · IEEE
Email: samarukmini07@gmail.com
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Abstract:

Requests for Information (RFIs) can delay and complicate large construction projects, yet their downstream effects on design revisions, field rework, and schedule are rarely traced. This paper proposes an RFI-to-field traceability framework for airport Project Management/Construction Management (PMCM) teams. The framework links each RFI to the resulting drawing revisions, field change orders (FCOs), Non-Conformance Reports (NCRs), rework, and critical-path delay across four project systems (Procore, Oracle Unifier, Primavera P6, and Bluebeam), and adds a leakage-aware classifier that assigns each RFI to a low, medium, or high impact class using only information available at submission. Because the logs of the motivating airport case are confidential, the framework is evaluated on a synthetic benchmark of 2,400 RFIs over 48 months with known ground-truth links; the results therefore validate the pipeline and are not empirical findings about real projects. The tiered linkage recovered 89%–99% of true links at each stage, with precision of 57%–96% (lowest for NCR and schedule links), and linkage-derived impact labels agreed with ground truth (Cohen's $\kappa = 0.88$). With a time-ordered split, the best early-warning model (random forest) reached a macro-F1 of 0.39 (95% CI 0.36–0.43) and ROC-AUC of 0.62 against a macro-F1 of 0.26 for a majority-class baseline, i.e., weak discrimination under the assumed noise. No cost or schedule saving is claimed; replication on anonymized real logs with a manual link audit is required.

Index Terms: Data-driven model; requests for information (RFIs); record linkage; predictive analytics; construction rework; schedule delays; airport megaprojects; synthetic benchmark.

1. Introduction

The construction industry plays a major role in infrastructure development projects and seeks digital tools to manage construction project delivery and processes more effectively (Olawumi & D. W. M. Chan, 2019), (Kocakaya, Namlı, & Ü. Işıkdağ, 2019). The problems in these complex megaprojects, such as airport construction and other infrastructure projects, are extensive, interdependent, and long-lasting (Soliman, Alrasheed, Alghanim, & E. Morsi, 2019). Digital construction management and predictive construction analytics are beginning to address these complexities by reducing inherent risks. Requests for Information (RFIs), one of the most significant methods of technical communication for project decision-making, are associated with inefficiency in complex construction projects,

including cost overruns and delays. Although RFIs clarify design differences and field issues, others view them as non-value-adding activities that can add risks such as delays and cost overruns (Afzal, Wong, & A. A. Fard Fini, 2024). Traceability of upstream-to-downstream impacts on field execution, design-related RFIs, rework, schedule, and cost is limited, particularly for complex projects. This gap results in poor proactive project management and, more commonly, reactive attempts to solve problems that negatively affect the project. Rework, especially, is a frequent construction problem, that the literature links to schedule delay and cost overruns (Section II-C).

As digital construction platforms have evolved, linking data from several project systems to an RFI-to-field impact model has become a consistent research aim. Available RFI management platforms offer limited analytical capability for tracing how individual RFIs propagate into revisions, rework, and schedule loss (Afzal, Wong, & A. A. Fard Fini, 2024). The literature discusses the value of RFI frequency and turnaround time (Aibinu, Carter, Francis, & P. Vaz-Serra, 2019) and RFI response in relation to alternative delivery systems (Papajohn & M. El Asmar, 2021). However, the literature lacks a full understanding of the relationship between RFI characteristics and impact beyond revisions, Non-Conformance Reports (NCRs), or quantifiable schedule delays. Digital technologies and data-driven methodologies, with their wider adoption, can enable proactive risk identification and mitigation (Soliman, Alrasheed, Alghanim, & E. Morsi, 2019); (Afzal, Wong, & A. A. Fard Fini, 2024).

Therefore, this paper develops a data-driven model that links RFIs to drawing modifications, field rework/NCRs, and schedule delays in airport megaprojects. Its contributions are: (1) a traceability framework with an explicit, tiered linkage protocol that connects an RFI to drawing revisions, FCOs, NCRs, and schedule activities and states the certainty of every link; (2) a quantification method that assigns each RFI to a low, medium, or high impact class using numeric rework and delay thresholds and that divides delay, rework, and cost among RFIs sharing a downstream record; and (3) a leakage-aware, time-ordered evaluation of an early-warning classifier that uses only information known when an RFI is submitted (Yilmaz, Ergen, & A. M. Citipitioglu, 2025); (Panahi, Kivlin, & J. Louis, 2023). Because the logs of the motivating case are confidential, the evaluation uses a synthetic benchmark with known ground truth; its results validate the pipeline rather than describe real projects.

The remainder of this paper is organized as follows. Section II reviews related work on RFI management, rework analysis, and predictive analytics in construction. Section III states the problem. Section IV presents the traceability framework, the linkage protocol, the impact-class definitions, the evaluation design, and the synthetic benchmark. Section V reports the results on the benchmark, and Section VI concludes and outlines future work.

2. Literature Review

2.1. RFI Management and Response Performance

Requests for Information (RFIs) are an essential communication tool in construction, and inefficient RFI handling risks project delays and extra costs. Research shows that the number of RFI events per day and the time to turn them around are generally higher for large, complex projects, such as airport megaprojects, than for smaller projects (Aibinu,

Carter, Francis, & P. Vaz-Serra, 2019). This response time can be even more of a problem in projects that have fewer users per organization. Researchers have explored the effect of RFI response time on project performance, and for highway projects, they have examined how delivery method affects response time (Papajohn & M. El Asmar, 2021). In addition, researchers have used quantifiable RFI qualities to compare cost and performance across project delivery methods in heavy civil construction projects A (Kim, Petrov, Lim, & S. Kim, 2021). Although they are crucial, current RFI management platforms often have inadequacies and lack the depth of analytics needed to reduce processing time and fully mitigate risk (Afzal, Wong, & A. A. Fard Fini, 2024).

2.2. Design Changes and Construction Impacts

Design changes are common in construction projects and may arise from changes in project scope or client requirements, design errors and omissions, and inadequate information flow; such changes can generate rework and contribute to project schedule delays (Othman & M. S. Ali, 2024); (Yap, Abdul-Rahman, & W. Chen, 2017). Problems can move from one stage to the next and can significantly affect project execution, particularly when raised or explained through RFIs. The implications of such design modifications, especially in complex Building Information Modeling (BIM)- based applications, are a relatively new research challenge, and some proposals suggest using Machine Learning to forecast downstream implications of design changes (Abdulfattah & et al., 2023). Communication and project learning play an important role in managing design changes and minimizing new ones by leveraging past project experience (Yap, Abdul-Rahman, & W. Chen, 2017). Conflicts often go undetected or unresolved because design information is not well aligned with real-time field information.

2.3. Rework and Delay Analysis

Rework significantly impacts the construction industry and regularly causes cost and schedule overruns (Hegazy, Said, & M. Kassab, 2011); (Ma, Jiang, Zhu, & J. Jia, 2019). Some studies have developed techniques that explicitly introduce rework into construction schedule analysis to provide more realistic project timelines (Hegazy, Said, & M. Kassab, 2011). Studies have contrasted evaluations of the reasons for project delays and their impact on the project schedule, showing that delays often result from similar project issues (Hwang & L. P. Leong, 2023). Beyond schedule impacts, rework has been linked to specific cost overruns, further underscoring its cost impact. Several new approaches have been proposed to create construction project schedules based on different rework scenarios to improve planning accuracy (Ma, Jiang, Zhu, & J. Jia, 2019). Expert systems based on simulation approaches have been used to assess the probability of schedule delay (G. K. Koulinas, 2020), and machine learning-based models have been used to predict liquidated damages due to project delays in highway construction projects (Alshboul, Shehadeh, Mamlook, Almasabha, Almuflih, & S. Y. Alghamdi, 2022).

2.4. BIM, Digital Construction, and Predictive Analytics

BIM and digital construction technologies show strong potential to improve RFI management and overall project performance [(Kocakaya, Namlı, & Ü. Işıkdağ, 2019); (Afzal, Wong, & A. A. Fard Fini, 2024); (Pinto & t al., 2026). In geotechnical or construction projects, however, BIM can support a more organized and collaborative RFI

process and, in turn, improve traceability and coordination (Pinto & t al., 2026). However, BIM projects still exist, and interoperability and workflow standardization remain issues (Afzal, Wong, & A. A. Fard Fini, 2024); (Pinto & t al., 2026). Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have been used in various ways in digital construction, such as design optimization, automation, and risk management (Akinosho & et al., 2020); (Baduge & et al., 2022); (Kor, Yitmen, & S. Alizadehsalehi, 2022). These technologies can also automatically create construction schedules using ML and BIM and support data-driven delay management processes (Al-Sinan, Bubshait, & Z. Aljaroudi, 2024).

The closest prior work to this study is the machine-learning framework of Yilmaz et al. (Yilmaz, Ergen, & A. M. Citipitioglu, 2025), who used 3,628 RFI documents from a large-scale airport project to predict RFI closure duration so that RFIs likely to remain open longer can be identified and prioritized. They compared five algorithms (support vector machine, logistic regression, k-nearest neighbors, decision tree, and random forest) using both categorical RFI metadata and textual data, and introduced the inputs in stages to simulate real project conditions. Prediction accuracy improved markedly once the first response durations were included, ranging from 59% to 92% across the models; support vector machines performed best with metadata alone, while decision trees performed best when response durations were added. The authors also note that such models can be integrated into common data environments for real-time RFI prioritization. Their work therefore shows that RFI closure behavior can be predicted from RFI data in an airport setting. However, its reported target is the RFI process itself (how long an RFI stays open), rather than tracing an answered RFI forward to drawing revisions, NCRs, field rework, or critical-path delay. The present study differs in three respects: the prediction target is the downstream impact class of an RFI rather than its closure time; the impact labels come from an explicit RFI-revision-FCO-NCR-schedule linkage built from four project systems; and the model is intended to flag RFIs that will cause rework and schedule loss rather than RFIs that will merely be slow to close.

Other recent studies apply information technology and language models to RFIs. Sandoval et al. (Sandoval, Bernardo, Dionisio, & A. H. Aquino, 2023) examine the use of information and communication technologies to optimize the RFI process, Panahi et al. (Panahi, Kivlin, & J. Louis, 2023) propose an RFI recommender system for pre-construction design review that combines natural language processing, ChatGPT, and computer vision, and Joy et al. (Joy, Zarei, & M. Nik-Bakht, 2026) map RFIs to BIM elements using large language models. These works focus on how RFIs are processed, recommended, and linked to model elements rather than on measuring their downstream field outcomes.

Another under-finalized aspect is the relationship between RFI attributes, field work, non-conformance reports (NCRs), and schedule delays for a megaproject like an airport, using predictive analytics. The problem, while not solved, is how, with an approved RFI-to-field traceability model, to measure the rework, time, and cost on these complex megaprojects that are linked to information and design concerns recorded in RFIs.

3. Problem Statement

Project information is often encoded in different systems with conflicting data formats, making it difficult to integrate, process, and analyze project data and making it harder to track downstream impacts and work progress systematically (Afzal, Wong, & A. A. Fard Fini, 2024); (Bucher, Hunhevicz, Soman, Pauwels, & D. M. Hall, 2024). RFIs that are distributed are often hard to assimilate and analyze at a glance using existing RFI management platforms, which would ultimately miss out on thorough insights into potential risks.

This problem will be resolved only if a system can integrate the various pieces of RFI information and raise useful early-warning signals. This would allow proactive identification of high-impact design problems, specific measurement of their downstream impacts on revisions, field rework, and schedule delays, and, as a result, avoidable rework, delays, and associated costs within a project team (Soliman, Alrasheed, Alghanim, & E. Morsi, 2019); (Yilmaz, Ergen, & A. M. Citipitioglu, 2025). This data-driven approach aims to reduce the analytical chasm between RFI generation and its impact on project performance, promoting informed decision-making and improving project efficiency, especially for an airport megaproject. Such a system must also respect timing: an early-warning model may use only information that is known when the RFI is submitted.

4. Methodology

4.1. Research Design and Evaluation Strategy

The framework was designed around a retrospective case: the structural steel and concrete package of a multi-billion-dollar airport terminal concourse, in which RFIs, drawing revisions, change orders/NCRs, and schedule activities are recorded in four separate systems, namely Procore (RFI management), Oracle Unifier (change orders and NCRs), Primavera P6 (schedule), and Bluebeam (drawing revisions). The logs of that project are proprietary, and statistics computed from them cannot be released here. To give every quantitative claim in this paper an auditable basis, the framework is therefore evaluated on a synthetic benchmark: a simulated project of 2,400 design-related RFIs submitted over 48 months, generated with the same four-system record structure and with the true RFI–revision–FCO–NCR–activity links known by construction (Section IV-E). The full population is analyzed; no purposive or outcome-based sampling is used, so no sampling-error claim is made. All numbers in Section V are produced by the script that accompanies the paper. They validate the pipeline and are not empirical findings about real projects. Because the simulator embeds assumed relationships between RFI attributes and outcomes, accuracy and feature-importance results describe how the pipeline behaves under those assumptions, not what drives impacts on real projects.

Table 1. case project and synthetic benchmark characteristics

Characteristic	Description / Value
Total RFIs Analyzed	2,400 design-related RFIs, full synthetic population (no sampling)
Structural Package Scope	New concourse structural steel and concrete package, including foundations, seismic isolation systems, and composite steel-concrete elements

Characteristic	Description / Value
Project Duration	48 months (synthetic), from design finalization through substantial completion
Contract Value (motivating case)	Multi-billion-dollar airport terminal megaproject; structural package value withheld and not used in the benchmark
Data Collection Period	48-month synthetic window covering the full RFI lifecycle
Primary Data Sources	Procore (RFI management), Oracle Unifier (change orders/NCRs), Primavera P6 (schedule/CPM), Bluebeam (drawing revisions); record structure replicated in the synthetic logs
Data Type	Synthetic benchmark with known ground-truth links; seed 20261026; real-project logs not used

The structural package of the motivating case includes an elevated concourse, a composite steel-and-concrete design, and seismic isolation. The synthetic disciplines (structural steel, concrete and foundations, seismic isolation, architectural interface, MEP interface) and phases (foundations, substructure, superstructure, roof and envelope) follow that scope. The synthetic timeline covers the full RFI lifecycle, from first submission to the field change implemented months later. Table I summarizes the benchmark.

4.2. Data Collection and Preprocessing Pipeline

Synthetic logs were generated for the RFI log, drawing-revision log, FCO log, NCR log, and schedule-activity table, with imperfections that occur in practice. About 4% of RFIs lack a usable drawing reference. Downstream records cite the upstream record that caused them only part of the time: 62% of revisions cite their RFI(s), 85% of FCOs cite their revision, 70% of NCRs cite their FCO, and 90% of delayed activities cite their FCO. Unrelated records (design-initiated revisions, owner-directed FCOs, workmanship NCRs, and weather or procurement delays) share drawings, work zones, and time windows with RFI-driven records and are added at 0.9, 0.6, 1.5, and 2.0 times the number of true revision, FCO, NCR, and delayed-activity records, respectively. On a real project the preprocessing steps are: de-duplication; reconciling date and time-stamp inconsistencies across systems; harmonizing discipline categories and the subjective RFI priority scale; and building the key variables RFI response time (days), drawing revision count, rework hours, FCO and NCR flags, critical-path schedule delay (working days, from Primavera P6), and cost. Missing values are injected at the rates in Table 6 and handled inside the modeling pipeline: numeric variables are median-imputed and categorical variables mode-imputed with statistics from the training window only, and a missing-value indicator is added for each numeric variable. Imputation is therefore never fitted on test data, and a complete-case analysis is reported as a sensitivity check. Data consistency and completeness were checked with Pandas and NumPy, as shown in Fig. 1.

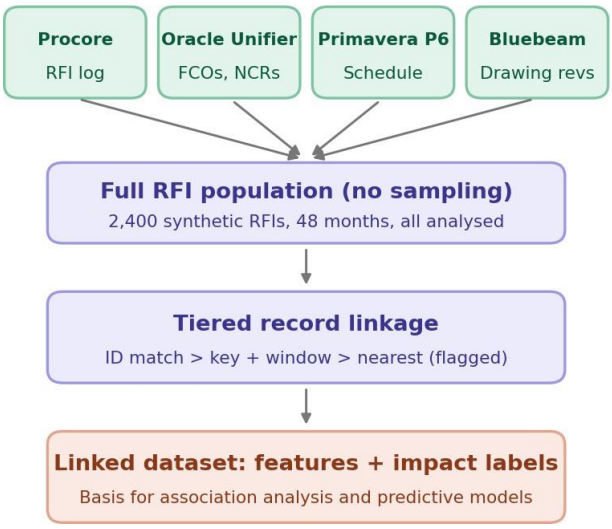


Fig. 1. Data sources and integration flow (the synthetic benchmark mirrors the four-system structure).

Fig. 1 shows the data flow. Records are pulled from the four systems, cleaned (duplicates removed, dates standardized, categories harmonized), and joined through the linkage protocol of Section IV-C into one analytical dataset covering the full RFI population. A final validation step flags every RFI whose chain contains a link made without an explicit identifier, so that the share of explicit, key-matched, and nearest-in-time links is always visible (Table 7). The resulting dataset supports the association analysis and the machine-learning models described below.

4.3. RFI-to-Impact Traceability Framework and Quantification

The core of the framework is a traceability linkage model that connects each RFI to its downstream records. It is a record-linkage model, not a causal model: it establishes which records are associated through identifiers, drawing numbers, work zones, and dates, and it does not by itself establish that the RFI caused the downstream outcome. Links are made stage by stage (RFI to drawing revision, revision to FCO, FCO to NCR, and FCO to affected schedule activity) in three tiers of decreasing certainty. Tier 1 is an explicit identifier: the downstream record cites the upstream record. Tier 2 applies when no identifier exists and exactly one downstream record carries the same drawing number (revision and FCO stages) or work-breakdown-structure zone (NCR and activity stages) within a stage-specific window after the upstream record (45, 60, 90, and 60 days, respectively). Tier 3 applies when several records meet the tier-2 rule: the one nearest in time is taken and the link is flagged as ambiguous. A downstream record that already cites a different upstream record is never a candidate. Many-to-many cases arise when two RFIs on the same drawing lead to one shared revision. The shared revision and everything downstream of it are then linked to both RFIs; the impact class of each RFI uses the full outcome of the chain, but delay, rework hours, and cost are divided equally among the RFIs

that share a record when totals are computed. Delay is attributed to an RFI only through its chain: the critical-path delay of a schedule activity linked to the RFI's FCO counts, whereas delay on unlinked activities does not. Because a linked activity may also have been delayed by other causes, this rule can overstate the delay attributed to RFIs, and the overstatement is measured against ground truth in Section V-G. On real data, links would also be audited manually on a stratified random sample of 200 links (50 per stage, oversampling tier-2 and tier-3 links), reviewed independently by two project engineers, and the audited precision of each tier would be reported; the synthetic benchmark replaces this audit with exact ground truth. The impact metrics are rework hours, FCO flag, number of drawing revisions, critical-path delay (working days), and cost (rework labor at an assumed $95 per hour plus FCO direct cost).

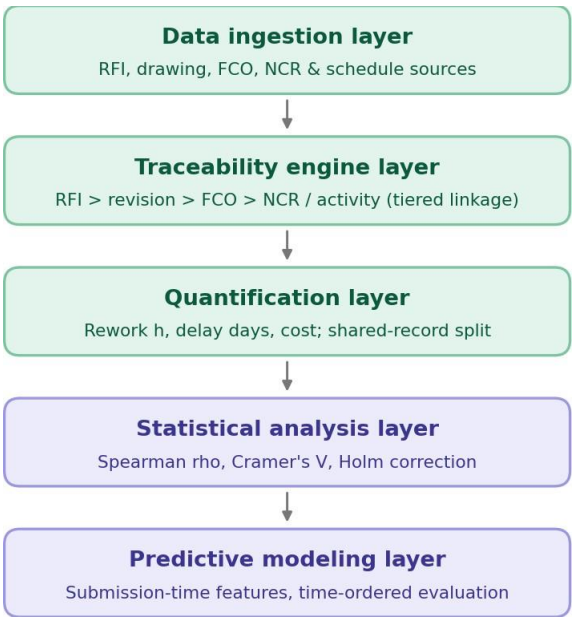


Fig. 2. Proposed five-layer RFI-to-impact traceability architecture.

Fig. 2 shows the five-layer architecture. The data ingestion layer moves records from the four systems into a data warehouse. The traceability engine layer applies the tiered linkage of Section IV-C. The quantification layer computes rework hours, delay days, revision counts, and cost for each RFI chain. The statistical analysis layer relates RFI attributes to impact class using Spearman rank correlation for ordinal and continuous attributes and Cramér's V with a chi-square test for categorical attributes (Pearson correlation is not used because the impact class is ordinal and several attributes are categorical), with Holm correction for multiple comparisons. The predictive modeling layer trains the classifiers described in Section IV-D. The layers can be deployed in stages during construction and connected to live data feeds.

4.4. Predictive Model Development and Validation

Each RFI is assigned one of three impact classes from its linked chain using the numeric thresholds in Table 2, applied in this order: high impact if the chain includes rework of at least 200 labor hours or at least 10 working days of critical-path delay; medium impact if it is not high and includes an FCO, rework of at least 40 labor hours, or at least 1 working

day of delay; and low impact otherwise (no downstream record, or a drawing revision only). Because the labels are computed from recorded quantities by fixed rules, they involve no subjective labeler. Their reliability is assessed instead as agreement between labels derived from the linked chain and labels derived from the true chain (accuracy, Cohen's κ, and linearly weighted κ), and by re-labeling with every threshold scaled by 0.75 and 1.25. On real data, two reviewers would also label a stratified sample of 200 RFIs independently from the source records, and inter-rater κ and the class balance would be reported.

Table 2. Impact Class Definitions and Numeric Thresholds

Class	Rule (checked in the order high, medium, low)	Typical downstream record
High	Rework ≥ 200 labor hours, or critical-path delay ≥ 10 working days	Major rework, critical-path delay
Medium	Not high, and FCO issued, or rework 40–199 labor hours, or critical-path delay 1–9 working days	FCO, moderate NCR rework
Low	Not high or medium: no linked downstream record, or drawing revision only (rework < 40 h, no FCO, no delay)	Revision only, or none

Candidate features and the time at which each becomes known are listed in Table 3. An early-warning model may use only information available when the RFI is submitted. RFI response time is known only after the RFI is answered, so it is excluded from the early-warning feature set (Set A) and appears only in a comparison set (Set B), which is a post-response model that estimates how much extra information the response time carries and is not an early-warning tool. Package complexity is a 1–5 index of the referenced drawing at issue, and prior revisions is the number of revisions of that drawing before the RFI date.

Table 3. Features, Timing of Availability, and Feature Sets

Feature	Type	Known at	Set A	Set B
Discipline	Categorical	Submission	Yes	Yes
Priority	Ordinal categorical	Submission	Yes	Yes
Feature	**Type**	**Known at**	**Set A**	**Set B**
Submittal phase	Categorical	Submission	Yes	Yes
Originator	Categorical	Submission	Yes	Yes
Question length (words)	Numeric	Submission	Yes	Yes
References specification	Binary	Submission	Yes	Yes
Number of attachments	Numeric	Submission	Yes	Yes
Package complexity (1–5)	Ordinal	Submission	Yes	Yes
Prior revisions of referenced drawing	Count	Submission	Yes	Yes
Days since drawing issue	Numeric	Submission	Yes	Yes
RFI response time (days)	Numeric	After response	No	Yes

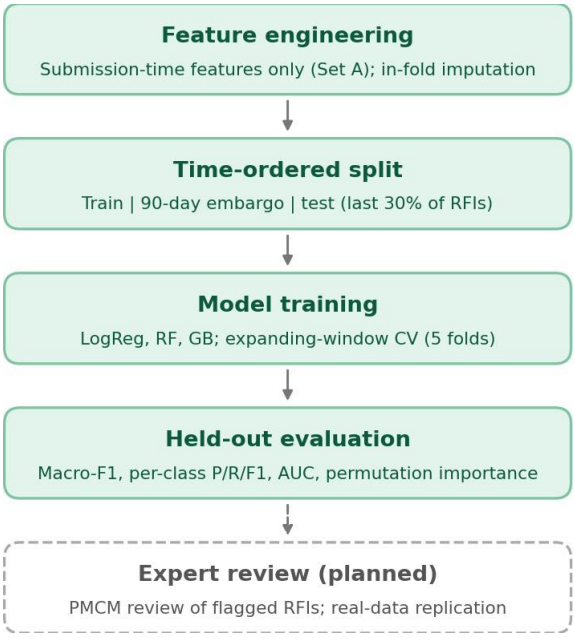


Fig. 3. Predictive model development and validation workflow.

Three multi-class classifiers are compared: multinomial logistic regression (baseline), a random forest (300 trees), and gradient boosting (200 trees, depth 3), all with class-balanced weighting because the class distribution is skewed and all with fixed hyperparameters, so that no tuning on the test set is possible. Categorical features are one-hot encoded, numeric features are imputed (and standardized for logistic regression), and every step sits inside one pipeline fitted on training data only. Because RFIs span 48 months and the model would be used prospectively, the data are split by submission date rather than at random. RFIs submitted before day 805 form the training window; RFIs submitted from day 895 onward (the last 30% of RFIs) form the test set; RFIs in between are dropped as a 90-day embargo, so that no training outcome was still unfolding when the test period began. Robustness is assessed with 5-fold expanding-window cross-validation inside the training window (each fold trains on earlier months and validates on the next, with a 60-day gap). The random 70/30 split and shuffled k-fold used in earlier drafts are no longer used. The model with the best cross-validated macro-F1 is chosen before the test set is examined. Test performance is reported as accuracy, balanced accuracy, macro-averaged and per-class precision, recall, and F1, and one-vs-rest ROC-AUC, with 95% bootstrap confidence intervals (1,000 resamples of the test set), confusion matrices, a majority-class baseline, and permutation feature importance on the test set. Fig. 3 summarizes the workflow. Expert review of flagged RFIs by PMCM practitioners is planned for the real-data replication and was not performed here.

4.5. Synthetic Benchmark Generator

Each synthetic RFI draws a discipline, priority, originator, question length, attachment count, specification-reference flag, and a referenced drawing (450 drawings in 40 work zones, each with a 1–5 complexity index); the submittal phase follows the submission date

with noise. A latent severity score combines assumed effects (larger for seismic isolation and for architectural and MEP interfaces, high priority, high package complexity, more prior revisions of the drawing, longer questions, and a shorter time since drawing issue) with random noise. Severity drives, through logistic and log-normal models, whether a drawing revision, an FCO, and an NCR follow, and how many rework hours, working days of critical-path delay, and dollars of cost result. Response time depends on priority, complexity, and severity. About 4% of RFIs lack a usable drawing reference, and unrelated records are added at the rates given in Section IV-B. The generator, its parameter values, and the random seed (20261026) are in the accompanying script, so every number in Section V can be regenerated. These relationships are assumptions, not estimates from real projects, and the noise is deliberately large so that observable attributes explain only part of the outcome: an oracle classifier given the latent severity would reach a one-vs-rest ROC-AUC of 0.81 for high impact, which bounds what any model using the observed attributes can achieve.

5. Results and Discussion

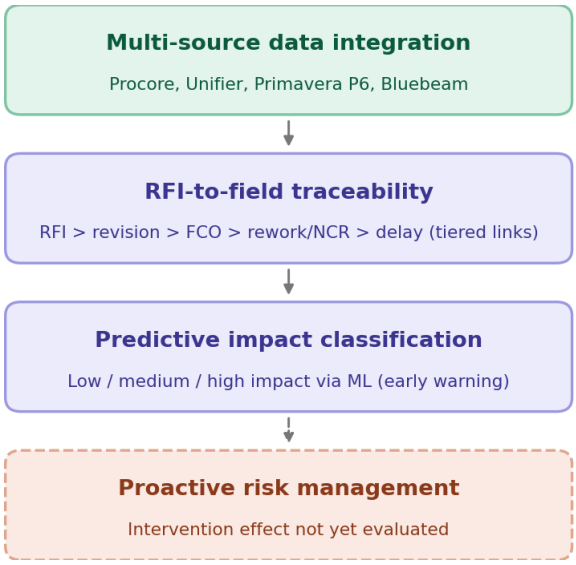


Fig. 4. Overview of the proposed RFI-to-field impact framework (intervention effects are not evaluated).

Table 4. Impact Categories, Traceability Mechanisms, and Intervention Opportunities

Impact Category	Traceability Mechanism	Measured Indicators	Intervention Opportunity	Project Phase	Ref.
Drawing Revisions	RFI-to-revision linkage tracking	Revision count, scope of change, affected disciplines	Design review re-prioritization	Design/Pre-constru ction	(Yap, Abdul-Rahman, & W. Chen, 2017); (Abdulfattah & et al.,

Impact Category	Traceability Mechanism	Measured Indicators	Intervention Opportunity	Project Phase	Ref.
					2023)
Non-Conformance Reports (NCRs)	NCR generation monitoring	NCR frequency, severity classification, resolution time	Quality control enhancement	Construction	This study
Field Rework	Physical execution documentation	Rework hours, material waste, labor redeployment	Construction re-sequencing	Construction/Com missioning	(Hegazy, Said, & M. Kassab, 2011); (Ma, Jiang, Zhu, & J. Jia, 2019)
Schedule Delays	Critical path impact assessment	Delay duration, milestone slippage, float consumption	Activity prioritization adjustment	All phases	(Hwang & L. P. Leong, 2023); (G. K. Koulinas, 2020)
Cost Escalation	Change order and budget variance analysis	Direct costs, indirect costs, contingency depletion	Procurement adjustment	All phases	(Kim, Petrov, Lim, & S. Kim, 2021)
Stakeholder Communication	Design interface conflict identification	Coordination meeting frequency, issue resolution time	Collaborative planning sessions	Design/Construction	(Yap, Abdul-Rahman, & W. Chen, 2017); 18]

Table 5. Comparison of RFI Traceability Approaches

Approach	Primary Focus	Measured Outcomes	Management Strategy	Traceability Scope	Source
Traditional RFI Baselines	RFI frequency and response time	Communication efficiency, closure duration	Reactive tracking of RFI volume	RFI submission to closure	(Aibinu, Carter, Francis, & P. Vaz-Serra, 2019); (Papajohn & M. El Asmar, 2021)

Approach	Primary Focus	Measured Outcomes	Management Strategy	Traceability Scope	Source
RFI-to-Field Framework	Downstream project impact	Drawing revisions, NCRs, field rework, schedule delays	Proactive risk management and early intervention	RFI attributes to physical execution outcomes	(Yap, Abdul-Rahman, & W. Chen, 2017); (Abdulfattah & et al., 2023); (Hegazy, Said, & M. Kassab, 2011); (Ma, Jiang, Zhu, & J. Jia, 2019)
Conventional RFI Analysis	Event documentation	RFI count by project type	Post-event analysis	Single-phase tracking	(Kim, Petrov, Lim, & S. Kim, 2021)
Approach	**Primary Focus**	**Measured Outcomes**	**Management Strategy**	**Traceability Scope**	**Source**
Proposed Traceability Model	Record-linkage chain mapping	Design interface conflicts, change orders	Predictive prioritization	Multi-phase impact propagation	(Soliman, Alrasheed, Alghanim, & E. Morsi, 2019); (Yilmaz, Ergen, & A. M. Citipitioglu, 2025) (Panahi, Kivlin, & J. Louis, 2023)

Fig. 4 and Tables 4 and 5 place the framework in the context of current RFI practice and give the qualitative mapping between impact categories, traceability mechanisms, and intervention opportunities. The remainder of this section reports the evaluation on the synthetic benchmark. Every table from Table 6 onward and every figure from Fig. 5 onward is generated by the accompanying script, and all statements concern the benchmark, not a real project.

5.1. Synthetic Benchmark and Descriptive Statistics

The benchmark contains 2,400 RFIs. Of these, 1,417 (59.0%) led to at least one drawing revision, 765 (31.9%) to an FCO, 506 (21.1%) to NCR rework, and 296 (12.3%) to critical-path delay; 30 of 1,387 revisions were shared by two RFIs. Using the labels derived from the linked chains (Table 2), the classes are distributed as low 1,626 (67.8%), medium

511 (21.3%), and high 263 (11.0%); the labels derived from the true chains give 1,635, 549, and 216. Table 6I gives descriptive statistics and the missing-data rate of each variable; 24.0% of RFIs have at least one missing value. By discipline, 31.5% of RFIs concern structural steel, 27.0% concrete and foundations, 17.6% architectural interfaces, 16.0% MEP interfaces, and 7.9% seismic isolation; by priority, 58.9% are normal, 20.6% high, 13.1% low, and 7.4% critical. Median response time rises from 6 days for low-impact RFIs to 7 days for medium and 8 days for high-impact RFIs.

Table 6. Descriptive Statistics and Missing-Data Rates (Synthetic Benchmark, N = 2,400)

Variable	Median [Q1–Q3]	Mean (SD)	Missing (%)
RFI response time (days), post-response	7 [4–10]	7.9 (5.0)	3.5
Question length (words)	45 [30–67]	53.5 (35.4)	1.4
Package complexity (1–5)	3 [2–4]	2.8 (1.2)	6.2
Prior revisions of drawing	1 [1–2]	1.6 (1.3)	4.0
Days since drawing issue	67 [38–107]	79.6 (56.7)	8.5
Number of attachments	1 [0–2]	1.2 (1.1)	2.5
Priority (categorical)	—	—	0.7

5.2. Linkage Performance

Table 7 reports, for each stage, the number of true links, the number of links the protocol made, recall, precision, and the number of links produced by each tier with that tier's precision. Recall was high at every stage (95.5% for RFI to revision, 99.3% for revision to FCO, 89.1% for FCO to NCR, and 97.6% for FCO to schedule activity), so most chains can be reconstructed. Precision fell downstream: 91.7%, 96.0%, 66.1%, and 57.4%, respectively. The cause is visible in the tiers. Explicit identifiers were always correct, but only because the generator creates citations without typing errors; real logs contain mistyped identifiers, so tier-1 precision on real data would be lower. Tier-2 and tier-3 links were much less reliable for NCRs (precision 34% and 27%) and for schedule activities (10% and 9%), because unrelated NCRs and delayed activities in the same work zone and time window are easily mistaken for RFI-driven ones. Of the 336 ambiguous (tier-3) links, most are wrong, which is why they are flagged rather than silently accepted.

Table 7. Linkage Performance by Stage Against Ground Truth (Synthetic Benchmark)

Stage	True links	Links made	Recall	Precision	Tier 1 n (prec.)	Tier 2 n (prec.)	Tier 3 n (prec.)
RFI to revision	1,417	1,476	95.5%	91.7%	866 (100%)	537 (84%)	73 (49%)
Revision to FCO	747	773	99.3%	96.0%	638 (100%)	127 (80%)	8 (38%)
FCO to NCR	495	667	89.1%	66.1%	346 (100%)	131 (34%)	190 (27%)
FCO to schedule activity	291	495	97.6%	57.4%	262 (100%)	168 (10%)	65 (9%)

5.3. Reliability of the Impact Labels

Labels derived from the linked chain matched labels derived from the true chain for 94.3% of RFIs (Cohen's $\kappa = 0.88$; linearly weighted $\kappa = 0.89$). Most disagreements came from false downstream links: 54 of 549 truly medium-impact RFIs (9.8%) were labeled high because a wrongly linked NCR or delayed activity added rework or delay, and 32 of 1,635 truly low-impact RFIs (2.0%) were labeled medium. Scaling every threshold in Table II by 0.75 and by 1.25 changed only 3.2% and 2.6% of the labels, respectively, so the class boundaries are not a sensitive choice in this benchmark.

5.4. Association between RFI Attributes and Impact Class

Table 8 relates each attribute to the ordinal impact class (low, medium, high) using Spearman's ρ for ordinal and continuous attributes and bias-corrected Cramér's V for categorical attributes, with Holm correction across the 11 tests. Package complexity ($\rho = 0.23$), prior revisions ($\rho = 0.15$), question length ($\rho = 0.12$), and days since drawing issue ($\rho = -0.08$) were associated with impact class after correction (Holm $p < 0.01$), and priority only weakly ($\rho = 0.06$, Holm $p = 0.025$). Response time, which is known only after the RFI is answered, was associated with impact ($\rho = 0.19$) and is shown for completeness. Discipline was weakly associated ($V = 0.06$, Holm $p = 0.011$); submittal phase, originator, attachments, and specification reference were not significant after correction. All associations are weak ($|\rho| \leq 0.23$). They are associations, not causal effects, and in this benchmark they reflect the effects assumed in the generator.

Table 8. Association Between RFI Attributes and Impact Class (Synthetic Benchmark)

Attribute	Method	Statistic	p	Holm-adjusted p
Priority (ordinal)	Spearman ρ	0.06	0.005	0.025
Package complexity	Spearman ρ	0.23	<0.001	<0.001
Prior revisions	Spearman ρ	0.15	<0.001	<0.001
Question length (words)	Spearman ρ	0.12	<0.001	<0.001
Days since drawing issue	Spearman ρ	-0.08	<0.001	0.001
Attachments	Spearman ρ	0.04	0.054	0.162
References spec	Spearman ρ	-0.03	0.215	0.430
Response time (post-response)	Spearman ρ	0.19	<0.001	<0.001
Discipline	Cramér's V	0.06	0.002	0.011
Submittal phase	Cramér's V	0.04	0.018	0.073
Originator	Cramér's V	0.01	0.305	0.430

5.5. Predictive Performance on Held-Out Data

The test set contains 722 RFIs submitted after the embargo (low 475, medium 157, high 90), and the training window contains 1,482. The random forest had the best cross-validated macro-F1 (0.40 ± 0.03) and was therefore the model carried forward. On the test set it reached macro-F1 0.39 (95% CI 0.36–0.43), balanced accuracy 39.3%, and ROC-AUC 0.62 (95% CI 0.58–0.65); logistic regression and gradient boosting reached macro-F1 of 0.30 and 0.33 (Table 9). The majority-class baseline has a higher accuracy (65.8% versus 55.7% for the random forest) but a macro-F1 of only 0.26 and balanced accuracy of 33.3%,

because it never predicts the medium or high class; macro metrics are therefore the appropriate yardstick, and the models beat the baseline on them only modestly.

Table 10 and Fig. 5 break the result down by class. Per-class results are reported for the random forest, the best-performing model; the logistic regression and gradient boosting models are compared on overall metrics only (Table 9). High-impact RFIs, the class that matters most for early warning, were found with recall 0.19 and precision 0.22 (F1 0.20; one-vs-rest AUC 0.64, Fig. 6): of 90 high-impact RFIs in the test period, 17 were flagged high, and of 78 RFIs flagged high, 17 truly were. The model is thus a weak screening aid and not a reliable classifier. This is well below the oracle ceiling of 0.81 for high impact (Section IV-E), because the observable attributes explain only part of the latent severity. Adding the post-response RFI response time (Set B) raised the random forest's macro-F1 to 0.40 and AUC to 0.64, inside the confidence interval of Set A. Three checks suggest the result is not an artifact of data handling: the macro-F1 against ground-truth labels was 0.40; restricting the test set to the 575 RFIs with no missing values gave 0.40; and the test macro-F1 is consistent with the cross-validated value.

Table 9. Model Comparison on the Time-Ordered Test Set (Synthetic Benchmark)

Model	Feature set	CV macro-F1	Accuracy (%)	Balanced acc. (%)	Test macro-F1	Test ROC-AUC
Majority class	—	—	65.8	33.3	0.26	0.50
Logistic regression	A (submission)	0.37 ± 0.05	31.4	37.4	0.30	0.57
Random forest	A (submission)	0.40 ± 0.03	55.7	39.3	0.39	0.62
Gradient boosting	A (submission)	0.37 ± 0.02	38.8	39.2	0.33	0.59
Logistic regression	B (post-response)	0.38 ± 0.04	30.9	36.8	0.29	0.58
Random forest	B (post-response)	0.40 ± 0.03	56.4	40.3	0.40	0.64
Gradient boosting	B (post-response)	0.39 ± 0.02	39.1	38.0	0.33	0.60

Table 10. Per-Class Results for the Random Forest (Feature Set A)

Class	Test n		Precision	Recall	F1	ROC-AUC (OvR)
Low	475		0.73	0.72	0.73	0.68
Medium	157		0.24	0.27	0.25	0.54
High	90	0.22	0.19	0.20	0.64	

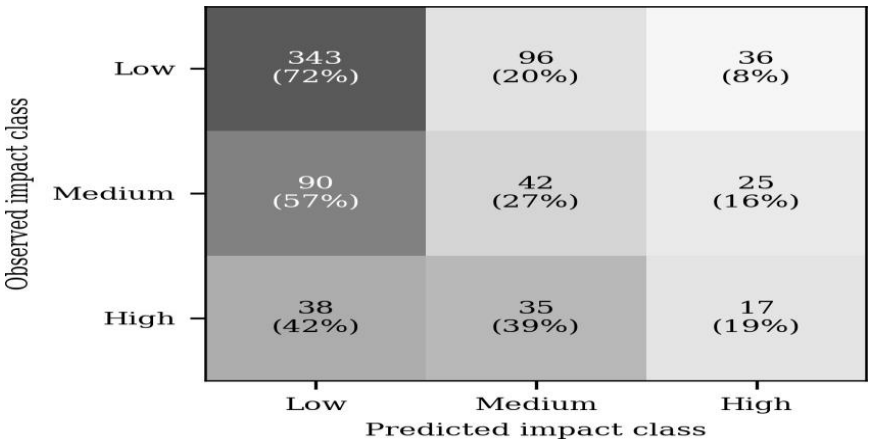


Fig. 5. Confusion matrix of the early-warning random forest (feature Set A) on the test period; rows are linkage-derived labels.

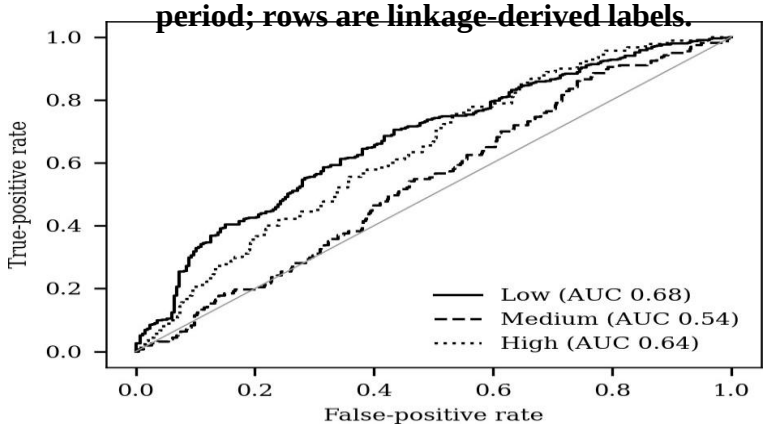


Fig. 6. One-vs-rest ROC curves of the early-warning random forest (feature Set A) on the test period.

5.6. Feature Importance

Fig. 7 shows permutation importance, the drop in test macro-F1 when one feature is shuffled (30 repeats). Only package complexity (0.032 ± 0.012) and prior revisions of the drawing (0.015 ± 0.008) are clearly above zero; every other feature is within one standard deviation of zero or below it. In Set B the importance of response time was 0.015 ± 0.017, not distinguishable from zero. The generator assigned non-zero effects to discipline, priority, phase, and question length as well, so their absence here shows how hard it is to detect small effects from 1,482 training RFIs under heavy noise; it is not evidence that these attributes are unimportant on real projects, and the importances of complexity and prior revisions describe the generator, not real projects.

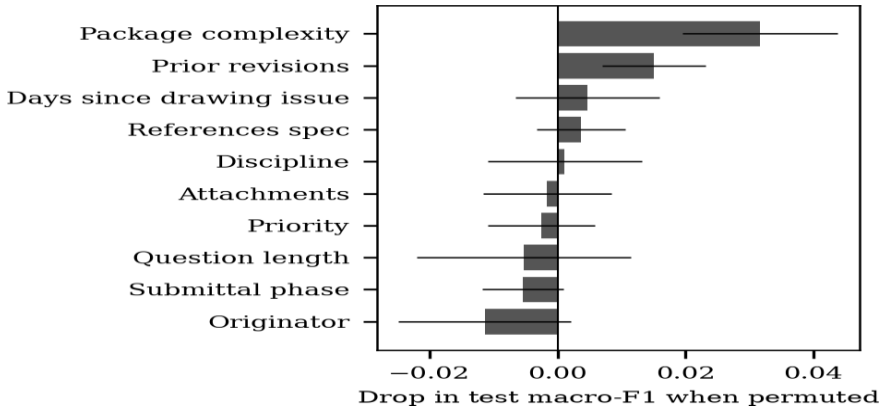


Fig. 7. Permutation importance of early-warning features (random forest, test period; bars show ± 1 SD over 30 repeats).

5.7. Traced Delay, Rework, and Cost

Table 11 compares the totals the linkage assigns to RFIs (with delay, rework, and cost divided among RFIs that share a record) with the ground truth. The linked chains assign 3,845 working days of critical-path delay to RFIs against a true 3,204, an overstatement of 20%, because false activity links (tier-2 and tier-3 precision about 10%) pass other-cause delay on to RFIs. Rework hours and cost are slightly understated (-4.9% and -4.0%) because some true NCR links are missed. These are properties of a simulated project and are not evidence of real cost or schedule exposure; the point is that delay attribution from unreviewed tier-2 and tier-3 links is biased upward, which is why Section IV-C requires manual review before delay is charged to an RFI.

Table 11. Delay, Rework, and Cost Traced to RFIs: Ground Truth Versus Linked Chains (Synthetic Benchmark)

Quantity	Ground truth	Linked chains	Difference
Critical-path delay (working days)	3,204	3,845	+20.0%
Rework (labor hours)	86,518	82,301	-4.9%
Cost (USD, rework labor + FCO direct cost)	$25.97M	$24.92M	-4.0%
RFIs with at least one drawing revision	1,417	1,476	+4.2%
RFIs with an FCO	765	774	+1.2%

5.8. Comparative Analysis with RFI Baselines

Past RFI studies mainly focused on RFI frequency and response time as indicators of process performance, with little attention to the content of RFIs and its association with downstream outcomes (Afzal, Wong, & A. A. Fard Fini, 2024); (Aibinu, Carter, Francis, &

P. Vaz-Serra, 2019); (Papajohn & M. El Asmar, 2021); (Joy, Zarei, & M. Nik-Bakht, 2026). The closest machine-learning study, (Yilmaz, Ergen, & A. M. Citipitioglu, 2025), predicts RFI closure duration from RFI metadata and text and reports accuracies of 59% to 92% across models once first-response durations are included; the present framework predicts the downstream impact class of each RFI (revisions, NCRs/rework, and schedule delay). The two targets, datasets, and metrics differ, so those figures cannot be compared with the results in Table 9. What the framework adds is a record of effects that standard RFI administration studies often omit (drawing revisions, NCRs, field rework, and critical-path delay) and an explicit statement of the certainty of each link through its tier; whether that record predicts anything on real projects remains to be shown.

5.9. Interpretation of Results

The benchmark shows what the pipeline can and cannot deliver. Linkage recall is high, so most RFI chains can be reconstructed, but precision is much lower for NCR and schedule links, so any deployment should report link tiers and treat tier-2 and tier-3 links as candidates for manual review before delay or cost is charged to an RFI. The early-warning classifier separates the impact classes only weakly under the assumed noise, so at best it could help rank RFIs for review; whether real RFI attributes carry more signal than the synthetic ones is an empirical question that only real data can answer. If they do, flagged RFIs could be used to reorder design reviews, resequence work, and identify design interfaces associated with disputes [(Soliman, Alrasheed, Alghanim, & E. Morsi, 2019); (Yilmaz, Ergen, & A. M. Citipitioglu, 2025); (Panahi, Kivlin, & J. Louis, 2023); (Pinto & t al., 2026), but no intervention effect was measured here and none is claimed.

5.10. Limitations

Several limitations apply. (1) All quantitative results come from a synthetic benchmark whose relationships are assumptions of the generator, so they validate the pipeline and do not describe real projects; the missing-data mechanism is also simulated as completely at random, whereas missingness in real RFI logs is unlikely to be completely at random. (2) The framework was designed around a single airport case, which limits external validity across delivery methods, structures, and contract types (Papajohn & M. El Asmar, 2021); 26, 27, 28]. (3) The linkage establishes association, not causation: unrelated causes of rework and delay exist on

every site, and delay attribution through linked activities is biased upward (Section V-G). (4) Explicit-identifier links are error-free in the generator, which overstates tier-1 reliability. (5) The impact thresholds and the linkage windows (45, 60, 90, and 60 days) are project-specific assumed values; the thresholds were not sensitive here, but both should be set with project stakeholders and calibrated against the real RFI-response and revision cycle. (6) Hyperparameters were fixed rather than tuned, and a single time-ordered test period was used. (7) No manual link audit, inter-rater labeling study, or expert review of flagged RFIs was performed. (8) RFIs submitted near the end of the data window may have downstream records that fall after the window closes, so their impact labels may be incomplete (right-censoring). The framework, variables, and procedures are described in full, and the accompanying script can be pointed at anonymized real logs to repeat the analysis; replication on real data is required before any claim about real performance, cost, or schedule benefit.

6. Conclusion and Future Work

A data-driven traceability system is needed to link Requests for Information (RFIs) to the resulting design modifications and field outcomes. This paper proposed such a framework, with a tiered, auditable linkage protocol, numeric impact classes, and a leakage-aware, time-ordered early-warning model, and evaluated it on a synthetic benchmark of 2,400 RFIs with known ground truth. The tiered linkage recovered 89%–99% of true links at each stage, but its precision fell to 66% for NCR links and 57% for schedule links, which overstated the delay attributed to RFIs by 20%; linkage-derived impact labels agreed with ground truth ($\kappa = 0.88$); and the early-warning model discriminated only weakly (macro-F1 0.39, ROC-AUC 0.62). These are pipeline-validation results, not evidence about real projects, and no cost or schedule benefit is claimed. Future work should (i) replicate the analysis on anonymized real logs with a manual audit of links and an inter-rater study of labels; (ii) have PMCM practitioners review the RFIs the model flags; (iii) improve linkage precision for NCR and schedule links, for example with work-package identifiers; (iv) add richer features such as RFI text and links to BIM elements (Joy, Zarei, & M. Nik-Bakht, 2026); and (v) adopt a design capable of supporting causal claims, such as matched comparisons of RFIs with and without a given attribute, before describing any relationship as causal.

REFERENCES

Abdulfattah, B. S., & et al. (2023). "Predicting implications of design changes in BIM-based construction projects through machine learning," . *Autom. Constr*, doi: 10.1016/j.autcon.2023.105057.

Afzal, M., Wong, J., & A. A. Fard Fini. (2024). "Towards digital approach for managing request for information (RFI) in construction projects: a literature review,". *Constr. Innov*, doi: 10.1108/ci-05-2023-0113. https://www.emerald.com/ci/article/25/5/1345/1252783.

Aibinu, A. A., Carter, S., Francis, V., & P. Vaz-Serra. (2019). "Request for information frequency and their turnaround time in construction projects,". *Built Environ. Proj. Asset Manag*, doi: 10.1108/bepam-10-2018-0130. https://www.emerald.com/bepam/article/10/1/1/63591.

Akinosho, T., & et al. (2020). "Deep learning in the construction industry: a review of present status and future innovations,". *J. Build. Eng*, doi: 10.1016/j.jobe.2020.101827.

Alshboul, O., Shehadeh, A., Mamlook, R. E., Almasabha, G., Almuflih, A. S., & S. Y. Alghamdi. (2022). "Prediction liquidated damages via ensemble machine learning model: Towards sustainable highway construction projects,". *Sustainability*, vol. 14, no. 15, Art. no. 9303, 2022, doi: 10.3390/su14159303.

Al-Sinan, M. A., Bubshait, A. A., & Z. Aljaroudi. (2024). "Generation of construction scheduling through machine learning and BIM: a blueprint," . *Buildings*, doi: 10.3390/buildings14040934.

Baduge, S. K., & et al. (2022). "Artificial intelligence and smart vision for building and construction 4.0: machine and deep learning methods and applications," . *Autom. Constr*, doi: 10.1016/j.autcon.2022.104440.

Bucher, D. F., Hunhevicz, J. J., Soman, R. K., Pauwels, P., & D. M. Hall. (2024). “From BIM to Web3: A critical interpretive synthesis of present and emerging data management approaches in construction informatics,”. *Advanced Engineering Informatics, vol. 62, Art. no. 102884,*, https://www.sciencedirect.com/science/article/pii/S1474034624005329.

G. K. Koulinas, A. X. (2020). "Schedule delay risk analysis in construction projects with a simulation-based expert system," . *Buildings*, doi: 10.3390/buildings10080134.

Hegazy, T., Said, M., & M. Kassab. (2011). "Incorporating rework into construction schedule analysis,". *Autom. Constr*, doi: 10.1016/j.autcon.2011.04.006. https://www.sciencedirect.com/science/article/pii/S0926580511000550.

Hwang, B.-G., & L. P. Leong. (2023). "Comparison of schedule delay and causal factors between traditional and green construction projects,". *Technol. Econ. Dev. Econ*, doi: 10.3846/20294913.2013.798596.

Joy, L. P., Zarei, F., & M. Nik-Bakht. (2026). “Semantic mapping of Request for Information (RFI) to BIM elements with large language models,” in. *Proc. 2026 European Conf. Computing in Construction (EC³), Corfu, Greece, Jul.* , 12–15, doi: 10.35490/EC3.2026.337.

Kim, J. J., Petrov, A., Lim, J., & S. Kim. (2021). "Comparing cost performance of project delivery methods using quantifiable RFIs: cases in California heavy civil construction projects,". *Int. J. Civ. Eng*, doi: 10.1007/s40999-021-00658-0.

Kocakaya, M. N., Namlı, E., & Ü. Işıkdağ. (2019). "Building information management (BIM), a new approach to project management," . *J. Sustain. Constr. Mater. Technol*, doi: 10.29187/jscmt.2019.36.

Kor, M., Yitmen, İ., & S. Alizadehsalehi. (2022). "An investigation for integration of deep learning and digital twins towards Construction 4.0,". *Smart Sustain. Built Environ*, doi: 10.1108/sasbe-08-2021-0148.

Ma, G., Jiang, S., Zhu, T., & J. Jia. (2019). "A novel method of developing construction projects schedule under rework scenarios,". *Sustainability*, doi: 10.3390/su11205710.

Olawumi, T. O., & D. W. M. Chan. (2019). "Building information modelling and project information management framework for construction projects,". *J. Civ. Eng. Manag*, doi: 10.3846/jcem.2019.7841. https://journals.vilniustech.lt/index.php/JCEM/article/download/7841/6987.

Othman, A. A., & M. S. Ali. (2024). “Managing design changes through integrating concurrent engineering into the architectural design process,”. *Int. J. Eng.Res. Afr*, vol. 70, pp. 117–140, https://buescholar.bue.edu.eg/cgi/viewcontent.cgi?article=1255&context=arch_eng.

Panahi, R., Kivlin, J.-P., & J. Louis. (2023). “Request for Information (RFI) recommender system for pre-construction design review application using natural language processing, Chat-GPT, and computer vision,”. *in Computing in Civil Engineering*, Data, Sensing, and Analytics, Corvallis, OR, USA, 2024, pp. 159–166.

Papajohn, D., & M. El Asmar. (2021). "Impact of alternative delivery on the response time of requests for information for highway projects,". *J. Manag. Eng*, doi: 10.1061/(asce)me.1943-5479.0000866. https://ascelibrary.org/doi/abs/10.1061/(ASCE)ME.1943-5479.0000866.

Pinto, H. A., & t al. (2026). "A review on BIM's contribution to an efficient RFI management in complex geotechnical and construction projects,". *Discov. Civ. Eng*, doi: 10.1007/s44290-026-00542-7.

Sandoval, I. S., Bernardo, J. P., Dionisio, S. R., & A. H. Aquino. (2023). "Application of Information and Communication Technologies (ICT) to optimize the request for information (RFI) process in construction projects,". *in Proc. 2023 9th Int. Conf. Innovation and Trends in Engineering (CONIITI), Bogotá, Colombia*, https://ieeexplore.ieee.org/abstract/document/10324094/.

Soliman, E., Alrasheed, K. A., Alghanim, S., & E. Morsi. (2019). "Integrating risk management and earned value framework to detect early warning signs—Case study,". *Journal of Engineering Research*, vol. 13, no. 3, pp. 2109–2116, 2025. https://www.sciencedirect.com/science/article/pii/S2307187724001421.

Yap, J. B., Abdul-Rahman, H., & W. Chen. (2017). "Collaborative model: managing design changes with reusable project experiences through project learning and effective communication,". *Int. J. Proj. Manag*, doi: 10.1016/j.ijproman.2017.04.010.

Yilmaz, N., Ergen, E., & A. M. Citipitioglu. (2025). "Enhancing RFI management in construction through machine learning-driven predictive models,". *Smart and Sustainable Built Environment*, pp. 1–21, 2025. https://www.emerald.com/sasbe/article/doi/10.1108/SASBE-05-2025.