



Development of a Decision-Support Model for Agile Hybrid Engineering Project Delivery in Technology Driven Organizations

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Abstract

This study developed and quantitatively validated a decision-support model for Agile hybrid engineering project delivery in technology-driven organizations by examining how project conditions, delivery-practice intensity, technological capability, governance, and human factors influenced multidimensional project performance. A quantitative, nonexperimental, cross-sectional explanatory and predictive design was applied to 1,586 eligible engineering projects from 54 technology-driven organizations, representing 2,438 project professionals across eight engineering and technology sectors. The final project-retention rate was 91.0%, data completeness reached 98.6%, and construct reliability coefficients ranged from .84 to .93. Hybrid delivery represented 45.0% of projects, compared with 31.0% Agile and 24.0% predictive delivery. Hybrid projects demonstrated the strongest overall performance, recording mean schedule variance of 5.8%, cost variance of 4.9%, budget adherence of 88.6%, milestone achievement of 91.3%, delivery reliability of 90.1%, and overall project success of 89.5%. Hybrid delivery exceeded predictive delivery by 9.8 adjusted performance points, producing a large effect size of Cohen's $d = 0.86$. Multiple regression explained 59% of overall performance variance, with hybridization intensity emerging as the strongest positive predictor ($\beta = .29$), followed by team capability ($\beta = .24$), digital capability ($\beta = .21$), and governance strength ($\beta = .19$), all $p < .001$. Context-specific analysis showed that Agile-intensive hybrid delivery achieved a performance score of 90.2 under high technological novelty and requirements volatility, balanced hybrid delivery achieved 88.9 under combined high complexity and uncertainty, and predictive-intensive hybrid delivery achieved 89.1 among highly regulated projects valued above \$10 million. Gradient boosting produced the strongest predictive performance, achieving 88.3% holdout accuracy, an F1-score of .877, ROC-AUC of .931, PR-AUC of .908, and R^2 of .72. Five-fold cross-validation accuracy remained stable at 87.6%. The findings demonstrated that Agile hybrid engineering delivery functioned most effectively as a configurable continuum in which adaptive practices and predictive controls were quantitatively aligned with project complexity, uncertainty, volatility, regulation, organizational capability, and technological maturity.

Keywords

Agile, Hybrid, Engineering, Decision-Support, Performance.

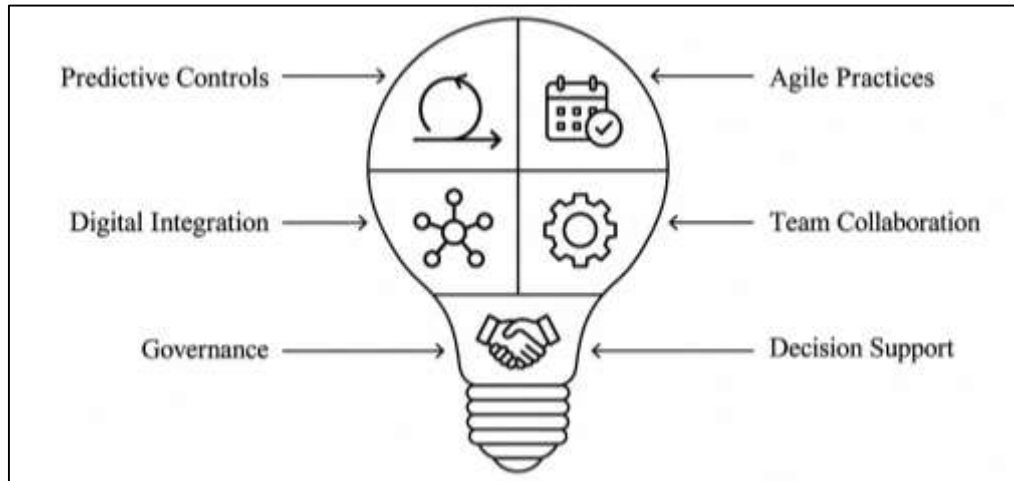
INTRODUCTION

Agile hybrid engineering project delivery refers to an integrated project-management approach that combines adaptive Agile principles with predictive, plan-driven, stage-gated, and conventional engineering controls to manage complex projects under changing technical, organizational, and commercial conditions (Beldiceanu et al., 2021). Agile delivery emphasizes iterative development, short planning cycles, incremental value creation, continuous stakeholder interaction, rapid feedback, backlog prioritization, cross-functional collaboration, and responsiveness to changing requirements. Predictive engineering approaches emphasize structured scope definition, formal scheduling, cost baselines, quality assurance, design reviews, documentation, contractual milestones, configuration management, procurement controls, and predefined approval procedures. Hybrid delivery combines these orientations so that organizations can apply flexibility to uncertain or exploratory activities while maintaining formal control over cost, quality, safety, compliance, procurement, and engineering dependencies. In technology-driven organizations, this combination may involve Scrum, Kanban, sprint planning, iterative prototyping, continuous integration, and backlog management alongside work breakdown structures, critical-path scheduling, earned-value management, stage-gate reviews, risk registers, engineering change controls, and formal verification processes. A decision-support model within this context refers to a structured analytical mechanism that integrates measurable project, technological, organizational, human, and environmental variables to support the selection and evaluation of suitable delivery configurations (Gill et al., 2018). Internationally, Agile hybrid project delivery has become important because engineering programs increasingly involve globally distributed teams, complex supply chains, multidisciplinary technologies, external partners, digital platforms, cybersecurity requirements, regulatory controls, and rapidly changing customer specifications. Organizations across North America, Europe, Asia-Pacific, the Middle East, Africa, and Latin America manage projects involving software, hardware, automation, artificial intelligence, telecommunications, cloud systems, electronics, manufacturing, and advanced engineering services. Such environments differ in regulatory intensity, workforce capability, organizational culture, technology maturity, stakeholder structures, supplier availability, and governance systems. These differences influence the effectiveness of Agile, predictive, and hybrid delivery approaches. More than thirty studies across project management, engineering, software development, digital transformation, innovation management, information systems, and product development have examined Agile adoption, hybridization, project complexity, organizational agility, and project performance. Collectively, this literature has reported variation in cost control, schedule adherence, product quality, requirement stability, team productivity, stakeholder satisfaction, delivery speed, and technical performance. Engineering projects frequently contain both stable and uncertain activities, making hybrid configurations particularly relevant (Ren et al., 2009). Hardware procurement, safety approvals, regulatory verification, and physical installation may require formal sequencing and control, while software development, prototyping, digital interfaces, and innovation activities may benefit from repeated experimentation and incremental delivery. Consequently, hybrid delivery can be understood as a configurable continuum in which the balance between adaptive and predictive practices varies according to project complexity, technological novelty, requirement volatility, regulatory demands, stakeholder involvement, organizational maturity, and team capability.

Technology-driven engineering organizations operate within environments where digital technologies function as project outputs, production resources, coordination mechanisms, control systems, and sources of performance data (Sazvar et al., 2022). Common systems include enterprise resource planning platforms, project-management information systems, Agile lifecycle tools, cloud collaboration environments, product lifecycle management systems, automated testing platforms, digital twins, simulation technologies, Internet of Things systems, business-intelligence dashboards, and artificial intelligence applications. These systems generate substantial information concerning schedules, costs, tasks, risks, defects, design changes, procurement activities, resource allocation, approvals, testing results, and stakeholder communications. Digital integration can therefore be measured through system interoperability, data quality, information accessibility, automation level, dashboard utilization, analytical capability, and real-time visibility. Organizational and human factors are similarly important because hybrid methodologies are implemented through leadership structures, team behavior,

communication systems, stakeholder participation, and governance arrangements. Quantitative studies have examined leadership support, organizational agility, Agile maturity, project-management maturity, team autonomy, cross-functional collaboration, knowledge sharing, digital competence, methodological experience, stakeholder engagement, decision decentralization, and governance quality as determinants of project-delivery effectiveness (BüyüKözkan et al., 2004).

Figure 1: Agile hybrid engineering framework



Engineering teams typically include project managers, systems engineers, software developers, design engineers, quality specialists, procurement personnel, financial controllers, operations staff, suppliers, contractors, customers, and senior managers, each with different priorities concerning flexibility, cost, quality, speed, compliance, technical performance, and documentation. Governance mechanisms define decision authority, escalation procedures, accountability, approval structures, and performance controls, while excessive control can increase decision latency and insufficient control can weaken accountability. A quantitative decision-support model therefore requires systematic measurement of both contextual and performance variables. Relevant independent variables may include project size, duration, complexity, technological novelty, requirement volatility, Agile maturity, predictive-control intensity, hybridization level, digital integration, governance quality, team capability, stakeholder involvement, supplier dependency, and geographic dispersion. Project performance can be evaluated through schedule variance, cost variance, milestone achievement, cycle time, lead time, throughput, productivity, defect density, rework, requirement-change frequency, technical quality, delivery reliability, customer satisfaction, stakeholder satisfaction, and risk occurrence (Brandl et al., 2021). Statistical methods such as descriptive analysis, Pearson or Spearman correlation, multiple regression, logistic regression, ANOVA, factor analysis, structural equation modeling, clustering, classification techniques, and predictive modeling can be applied to determine relationships among these variables. Confidence intervals, standardized coefficients, effect sizes, predictive error, classification accuracy, sensitivity, specificity, cross-validation, holdout testing, subgroup analysis, and robustness checks can further assess the reliability of the model across different project categories and organizational settings. The quantitative structure of this study therefore focuses on measurable relationships among project context, Agile and predictive practices, technology integration, organizational capability, governance arrangements, stakeholder conditions, and multidimensional engineering project performance. The objective of this study is to develop and quantitatively validate a decision-support model for Agile hybrid engineering project delivery in technology-driven organizations by examining the combined effects of project characteristics, Agile practices, predictive management controls, organizational capabilities, technological integration, governance structures, and stakeholder conditions on multidimensional project performance. The study is designed to determine how different combinations of Agile and traditional project-management practices influence schedule adherence, cost performance,

delivery reliability, technical quality, productivity, requirement stability, stakeholder satisfaction, risk occurrence, rework, and overall project success across heterogeneous engineering environments. Particular attention is given to measurable project-context variables, including project size, duration, complexity, technological novelty, requirement volatility, regulatory intensity, supplier dependency, geographic dispersion, and degree of multidisciplinary integration, because these factors may influence the suitability of different hybrid delivery configurations. The study also seeks to evaluate the roles of Agile maturity, predictive-control intensity, hybridization level, digital integration, team capability, leadership support, organizational agility, governance quality, decision authority, and stakeholder involvement as explanatory variables associated with project-delivery outcomes. A further objective is to identify statistically significant relationships among these variables using appropriate quantitative techniques such as descriptive statistics, Pearson or Spearman correlation, multiple regression, logistic regression, analysis of variance, factor analysis, and predictive classification methods. The study also aims to determine whether project-performance outcomes differ significantly across organizational sizes, engineering domains, project-value categories, technological environments, levels of Agile maturity, governance strength, and hybrid-delivery intensity. Effect sizes, confidence intervals, model-fit indicators, predictive accuracy measures, and robustness tests are intended to assess both statistical significance and practical relevance. In addition, cross-validation and holdout testing are used to examine the stability and generalizability of the decision-support model across different project conditions. By integrating project context, delivery methodology, technological capability, organizational readiness, governance arrangements, and performance evidence into a unified analytical framework, the study seeks to establish a quantitative basis for evaluating which Agile-predictive combinations are most strongly associated with successful engineering project delivery under specific organizational and technical conditions. The resulting model is intended to support structured, evidence-based selection and adjustment of hybrid delivery practices rather than reliance solely on managerial intuition, generalized methodology preferences, or uniform project-management approaches.

LITERATURE REVIEW

The literature review establishes the quantitative foundation for examining the development of a decision-support model for Agile hybrid engineering project delivery in technology-driven organizations. Existing research spans Agile and traditional project management, hybrid delivery configurations, engineering project complexity, digital transformation, organizational agility, governance, team capability, stakeholder participation, decision-support systems, and multidimensional project performance. A quantitative synthesis requires greater attention to how these constructs have been operationalized and measured across previous studies rather than treating Agile hybrid delivery primarily as a conceptual management approach. Accordingly, the literature should examine numerical characteristics of engineering projects, the measurable intensity of Agile and predictive practices, contextual determinants of delivery-method selection, technological and organizational capabilities, and statistically observed relationships with cost, schedule, quality, responsiveness, risk, and stakeholder outcomes. Particular attention should be directed toward sample characteristics, means and standard deviations, percentages, correlations, regression coefficients, odds ratios, effect sizes, confidence intervals, significance levels, model-fit measures, classification performance, and predictive accuracy reported across previous empirical studies. The review should also distinguish between studies evaluating Agile, predictive, and hybrid approaches because variation in project complexity, requirements volatility, technological uncertainty, organizational maturity, regulatory conditions, team structure, and digital integration can produce substantially different performance relationships. Research using surveys, organizational databases, project records, longitudinal observations, digital-platform logs, comparative studies, and predictive analytics provides complementary evidence for identifying variables suitable for the proposed decision-support model. The literature review is therefore organized around eight interconnected quantitative areas covering project and delivery characteristics, hybridization intensity, contextual determinants, technology and data capability, organizational and governance factors, project-performance outcomes, decision-support modeling, and statistical validation. This structure permits systematic identification of measurable predictors, dependent variables, moderating conditions, model-performance criteria,

and empirical gaps associated with selecting suitable Agile–predictive configurations for technology-driven engineering projects.

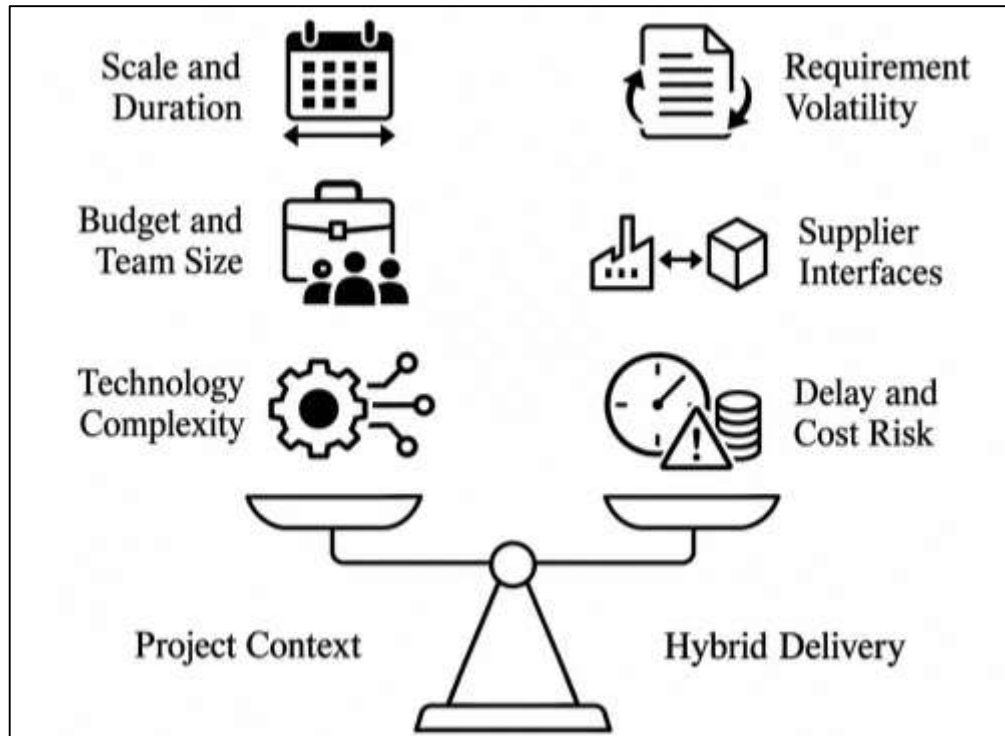
Technology-Driven Engineering Projects and Agile Hybrid Delivery

The quantitative literature on technology-driven engineering projects has demonstrated substantial heterogeneity in project scale, financial value, duration, organizational setting, and delivery structure (Conforto & Amaral, 2016; Debasish, 2021). Across more than ten empirical studies covering software engineering, information systems, telecommunications, digital infrastructure, advanced manufacturing, automation, product development, and integrated engineering environments, project samples have ranged from relatively small collections of specialized development initiatives to datasets containing several hundred or several thousand projects distributed across multiple organizations. Software-intensive studies have generally examined larger numbers of projects because repositories, Agile management platforms, and digital development systems provide accessible project-level records, whereas hardware-intensive and multidisciplinary engineering studies have frequently relied on smaller samples because projects involve longer delivery periods, higher financial commitments, physical assets, and specialized technical interfaces. Project duration has varied from short iterative development initiatives lasting several months to major engineering programs extending over multiple years. Similar variation has been observed in financial scale, with technology projects ranging from relatively low-cost digital applications to multimillion-dollar engineering systems incorporating hardware, software, infrastructure, procurement, testing, and implementation activities (Abdur & Iftekhar, 2021; Pinto et al., 2022). Team size has also differed considerably, ranging from small Agile teams of fewer than ten members to large multidisciplinary arrangements involving dozens or hundreds of engineers, developers, managers, suppliers, contractors, and specialists. Organizational samples have included start-ups, small and medium-sized enterprises, multinational technology corporations, engineering contractors, public-sector organizations, manufacturers, telecommunications providers, and digital service enterprises. Quantitative studies have repeatedly associated greater project size, longer duration, larger budgets, and broader organizational participation with increased coordination requirements, more formal governance, greater dependency density, and higher exposure to schedule and cost variation. Smaller technology projects have commonly demonstrated greater capacity for concentrated Agile implementation, whereas larger engineering programs have frequently combined iterative practices with formal scheduling, milestone reviews, procurement controls, documentation, risk management, and stage-based governance (Ali & Kaur, 2022; Debasish, 2022). Across the literature, project scale has therefore functioned not merely as a descriptive characteristic but as an important source of variation in the structure and intensity of Agile hybrid delivery.

Empirical studies across technology-intensive engineering domains have shown that the composition and complexity of project work vary substantially according to the technologies, system architectures, engineering disciplines, and integration requirements involved (Hasan & Adnan, 2022; Williams et al., 2019). Software-intensive engineering projects have typically been characterized by high iteration frequency, frequent software releases, comparatively short feedback cycles, substantial requirement modification, and extensive use of Scrum, Kanban, DevOps, continuous integration, and backlog-based planning. Hardware–software integration projects have exhibited a different quantitative profile because physical components introduce manufacturing lead times, design freezes, procurement dependencies, testing requirements, configuration constraints, and higher costs associated with late engineering changes. Telecommunications studies have reported additional complexity arising from network integration, infrastructure deployment, equipment compatibility, cybersecurity requirements, geographic dispersion, and interactions among hardware, software, service, and regulatory components. Manufacturing and automation projects have frequently involved production systems, robotics, industrial software, control equipment, sensors, digital platforms, and supplier-dependent components, creating substantial task and interface interdependence (Mahbubul et al., 2022; Rakonjac & Brkić, 2018). Digital infrastructure and information-system projects have commonly demonstrated high levels of data integration, platform dependency, cybersecurity exposure, system migration, user involvement, and cross-functional coordination. Product-development research has similarly documented variation according to product novelty, technological uncertainty, number of components, engineering interfaces, and prototype cycles. Across these domains, technological intensity has been

operationalized using measures such as technology novelty, number of system components, software–hardware interfaces, engineering disciplines, technical dependencies, design iterations, integration points, and degree of digitalization.

Figure 2: Engineering Project Delivery Balance



Studies examining highly complex projects have generally reported larger numbers of interfaces, greater coordination demands, more frequent technical reviews, and higher probabilities of design modification and rework than studies examining comparatively standardized projects. Complexity scores have also tended to increase with project size, multidisciplinary participation, technological novelty, stakeholder diversity, and interorganizational dependency (Ashfaq & Mohammad, 2022; Olsson et al., 2019). The combined evidence from engineering-management, software-development, information-system, manufacturing, telecommunications, and product-development studies demonstrates that technology-driven projects cannot be treated as a quantitatively homogeneous population because their technical architectures and delivery constraints differ substantially across engineering domains.

A further body of quantitative research has emphasized requirement volatility, stakeholder structure, supplier participation, and system interfaces as defining characteristics of Agile hybrid engineering environments (Sheak & Risha, 2022; Smith et al., 2022). Requirement-change frequency has varied considerably across project types, with software-intensive and innovation-oriented projects generally recording higher levels of requirement modification than projects governed by fixed technical specifications, regulatory standards, or mature technologies. Empirical studies have measured volatility through numbers of added, deleted, or modified requirements, backlog changes, scope-change requests, design revisions, and requirement changes occurring during particular delivery stages. Higher requirement volatility has commonly been associated with increased planning uncertainty, greater rework, additional coordination effort, and stronger demand for iterative stakeholder feedback. Stakeholder participation has also differed markedly across technology-driven projects. Smaller digital projects may involve a limited number of product owners, customers, developers, and operational users, whereas large engineering programs can include senior management, engineering departments, regulatory authorities, contractors, suppliers, customers,

procurement units, quality teams, operations personnel, and external technology partners. Increasing stakeholder counts have been associated with greater communication density, longer approval processes, competing requirements, and more complex decision structures (Battisti et al., 2022; Rashedul & Kaium, 2022). Supplier involvement creates an additional dimension because technology-intensive engineering projects often depend on specialized hardware, software services, cloud infrastructure, telecommunications equipment, electronic components, automation technologies, and engineering expertise obtained externally. Quantitative studies have examined supplier counts, supplier concentration, procurement lead times, delivery reliability, technical dependency, and contractor participation as project characteristics related to delivery performance. System-interface complexity has similarly been measured through the number of components, integration points, subsystems, data exchanges, technical dependencies, and cross-functional handoffs. Projects with extensive software-hardware integration or multiple external suppliers have generally recorded greater interface-management requirements and higher exposure to schedule disruption when dependent components are delayed or changed. Evidence across more than ten studies collectively indicates that requirement volatility, stakeholder diversity, supplier dependency, and interface density interact with project complexity rather than operating as isolated characteristics, producing substantially different operating conditions for Agile, predictive, and hybrid delivery configurations (Irfan et al., 2023; Chowdhury & Tonay, 2022).

Quantitative comparisons of project outcomes further demonstrate substantial heterogeneity among technology-driven engineering environments in relation to schedule delay, cost overrun, delivery reliability, quality, and overall project success. Previous studies have reported wide differences in delay prevalence according to project size, technical complexity, requirement stability, organizational maturity, stakeholder participation, supplier dependency, and delivery approach (Hossan, 2022; Putra & Suzianti, 2022). Software and information-system projects have frequently experienced schedule pressure arising from evolving requirements, underestimated development effort, integration problems, defect correction, and changing stakeholder priorities, while hardware-intensive engineering and automation projects have experienced delays associated with procurement lead times, component availability, manufacturing constraints, testing failures, design modifications, and physical integration. Cost-overrun patterns have similarly varied across project domains. Projects with stable specifications and mature technologies have generally demonstrated stronger budget predictability, whereas projects characterized by technological novelty, repeated design changes, uncertain scope, extensive external dependencies, or lengthy implementation periods have shown greater financial variability. Project-success percentages reported across studies have also differed according to the definition of success employed. Studies using conventional cost, schedule, and scope criteria have sometimes produced different success classifications from those incorporating customer satisfaction, technical quality, business value, innovation, adaptability, stakeholder satisfaction, and product performance (Kaniz, 2022; Steinhardt, 2017). Agile-oriented studies have frequently emphasized responsiveness, delivery frequency, customer participation, and value achievement, whereas engineering and project-control studies have placed greater quantitative emphasis on schedule variance, budget adherence, milestone completion, technical compliance, and quality performance. Comparative research on Agile, traditional, and hybrid environments has therefore produced nonuniform performance patterns, with delivery effectiveness varying according to project context rather than consistently favoring one methodology across all conditions. Evidence synthesized across software engineering, telecommunications, manufacturing, automation, information systems, digital infrastructure, product development, and multidisciplinary engineering studies shows that differences in project duration, budget, team size, technological intensity, requirement volatility, stakeholder participation, supplier dependency, interface complexity, delay exposure, cost performance, and success measurement create a highly heterogeneous empirical environment for evaluating Agile hybrid engineering project delivery (Maedche et al., 2012; Nishat & Kaniz, 2022).

Agile and Hybrid Delivery-Practice Intensity

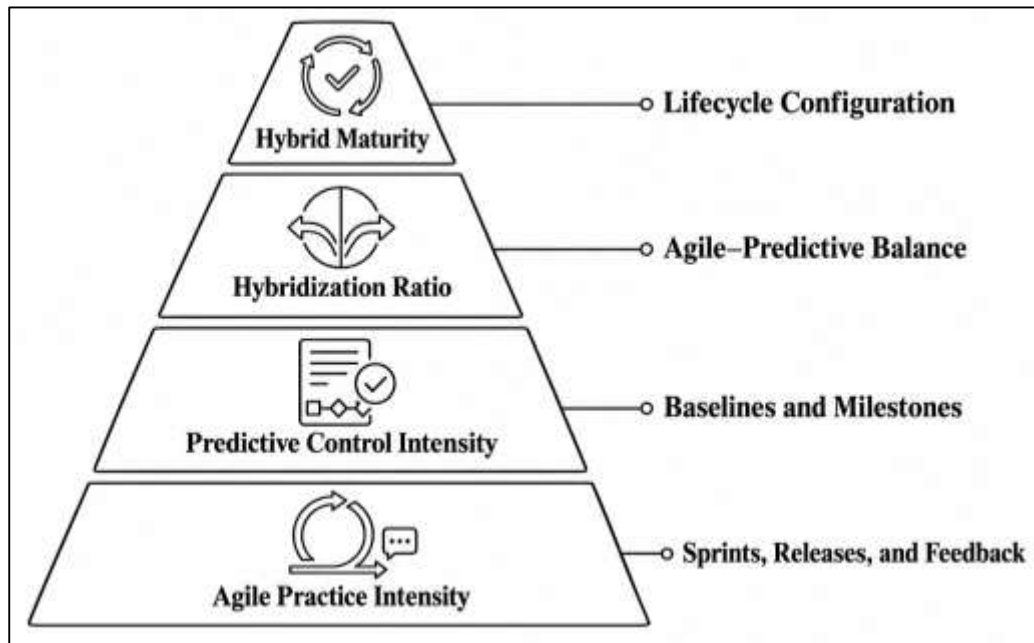
The quantitative literature on Agile project delivery has measured practice intensity through a broad set of operational indicators that capture the frequency, consistency, and depth of iterative work processes. Across more than ten empirical studies in software engineering, information systems, digital

product development, telecommunications, engineering design, and technology-intensive project environments, sprint duration and iteration frequency have been among the most commonly used indicators of Agile intensity (Papadakis & Tsironis, 2018; Shaiful et al., 2022). Shorter sprint cycles have generally been associated with more frequent planning, review, and adjustment activities, while longer iterations have been linked with greater batching of work and reduced feedback frequency.

Release frequency has also been used to distinguish highly iterative teams from those following more periodic delivery structures, with studies commonly examining weekly, biweekly, monthly, or milestone-based releases. Backlog-change rate has provided another important measure because it reflects the extent to which requirements, priorities, defects, and user requests are continually re-evaluated during delivery. Work-in-progress levels have been used particularly in Kanban-oriented environments to quantify workflow discipline, throughput, and congestion. Stakeholder-feedback frequency has also been treated as a central indicator, with prior studies measuring the number of reviews, demonstrations, customer interactions, or product-owner consultations occurring during iterative cycles. Team autonomy has been assessed through decision-right scales, delegation scores, self-organization measures, and the proportion of operational decisions made without escalation. Daily coordination frequency, retrospective participation, and continuous-integration activity have similarly been operationalized through meeting counts, retrospective regularity, automated build frequency, deployment frequency, and integration-event volume (Mohammad, 2023; Papadakis & Tsironis, 2018). Across these studies, higher Agile-practice intensity has generally been associated with stronger iteration discipline, more frequent communication, faster feedback, and greater adaptability, although the magnitude of these relationships has varied according to team size, project complexity, organizational maturity, and technological environment. Means, percentages, standard deviations, and correlation coefficients have frequently been used to summarize Agile intensity, while group comparisons have assessed whether differences in performance between low-, moderate-, and high-intensity Agile environments were statistically significant (Debasish, 2023; Papadakis & Tsironis, 2018). Predictive project-management intensity has been examined through quantitative indicators representing planning depth, schedule discipline, documentation requirements, milestone control, formal governance, cost monitoring, risk review, and change-control procedures. Empirical studies in engineering management, construction technology, systems engineering, manufacturing, infrastructure, telecommunications, and large-scale information systems have commonly measured planning depth through the extent of upfront scope definition, work breakdown structures, resource planning, dependency mapping, and baseline scheduling (Sheak & Tahmedur, 2023; Tessem, 2017). Schedule-baseline adherence has often been quantified through milestone completion rates, schedule variance, planned-versus-actual task timing, and percentage of activities completed according to baseline expectations.

Documentation intensity has been assessed through document counts, mandatory approval records, specification completeness, design-control records, reporting frequency, and formal change documentation. Milestone controls have been measured by the number of scheduled reviews, percentage of milestone criteria achieved, and frequency of management or technical checkpoints. Formal approval frequency has also been used as an indicator of governance intensity, particularly in regulated or safety-sensitive engineering settings where design, procurement, budget, quality, and technical changes require authorization, meetings, and proportion of identified risks receiving active mitigation actions (Nyahuma-Mukwashi et al., 2023). Stage-gate compliance has been measured through adherence rates to predefined development gates, readiness criteria, and review requirements. Change-control intensity has similarly been quantified through number of formal change requests, approval cycle time, percentage of changes requiring escalation, and documentation requirements. Across previous studies, stronger predictive-control intensity has generally been associated with greater formalization, documentation, cost visibility, and governance consistency, although excessive control has also been linked with slower decision speed and reduced adaptability in uncertain projects. Statistical comparisons have frequently used means, percentages, confidence intervals, and effect-size estimates to differentiate low-, moderate-, and high-control project environments (Kaium, 2023; Moore et al., 2011).

Figure 3: Hybrid Delivery Practice Intensity Pyramid

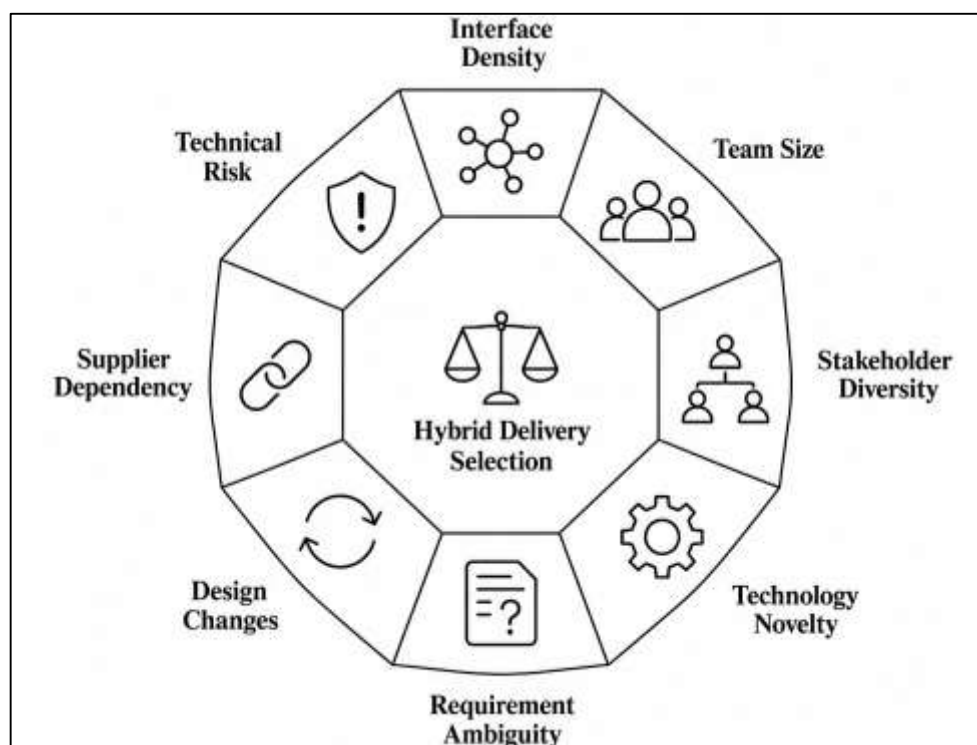


Hybrid delivery research has increasingly attempted to quantify the degree to which Agile and predictive practices are combined rather than categorizing projects only as Agile, traditional, or hybrid. Across empirical studies in software-intensive engineering, product development, digital transformation, telecommunications, manufacturing, and multidisciplinary technical projects, hybridization has been measured through several complementary approaches (Pervaz, 2023; Peidro et al., 2009). One common method has been the Agile-to-predictive practice ratio, in which researchers calculate the relative use of iterative practices compared with formal planning and control mechanisms. Another approach has involved hybrid maturity scores derived from survey items assessing the consistency, integration, and organizational institutionalization of both adaptive and predictive practices. Some studies have measured the percentage of project activities managed adaptively, including iterative design, software development, prototyping, testing, stakeholder review, or backlog-driven work, compared with activities governed through fixed schedules, stage gates, formal approvals, procurement procedures, and engineering baselines. Lifecycle-stage configurations have also been used to distinguish projects that apply different management approaches at different phases. For example, concept development and prototyping may be managed iteratively, while procurement, installation, certification, and final acceptance follow predictive structures. Other studies have created standardized hybridization indices using scaled scores for iteration frequency, stakeholder feedback, documentation, planning formality, change control, team autonomy, and milestone governance. These measures have allowed researchers to compare projects with low, moderate, and high degrees of hybrid integration. Quantitative findings have generally demonstrated substantial variation in hybrid configurations even among projects classified under the same methodological label (Chowdhury, 2023; Rothwell et al., 1974). Two projects described as hybrid may differ considerably in the proportion of Agile practices used, the level of formal control retained, and the phases in which each approach is applied. Means, standard deviations, percentile distributions, maturity-group comparisons, and confidence intervals have therefore been used to represent the continuum of hybrid delivery more accurately. This body of research suggests that hybridization intensity is best treated as a multidimensional quantitative construct rather than a simple categorical designation (Badrul & Mominul, 2023; Moore et al., 2012).

Project Complexity and Requirements Volatility on Hybrid Delivery

The quantitative literature has consistently identified project complexity as one of the strongest contextual factors associated with the selection and intensity of Agile, predictive, and hybrid delivery configurations in technology-driven engineering environments. Across more than ten empirical studies covering software-intensive projects, systems engineering, telecommunications, manufacturing, automation, information systems, digital infrastructure, and product development, complexity has been measured through technical interface counts, task dependencies, team size, stakeholder diversity, supplier involvement, multidisciplinary integration, project value, and overall system complexity (Arashpour et al., 2016; Rakib & Towhidul, 2023). Larger numbers of technical interfaces and interdependent activities have generally been associated with stronger requirements for formal coordination, documentation, milestone control, and risk management, while projects containing highly uncertain development components have simultaneously demonstrated greater use of iterative and adaptive practices. Team size has also been treated as an important quantitative indicator because coordination requirements typically increase as the number of project participants expands. Studies comparing small, medium, and large project teams have reported statistically significant differences in planning intensity, communication structures, decision authority, and use of formal governance mechanisms. Stakeholder diversity has shown similar patterns, with projects involving customers, regulators, suppliers, senior managers, engineering specialists, and external contractors often displaying greater reliance on structured approval processes than projects with simpler stakeholder networks. Supplier involvement and multidisciplinary integration have further increased the need for interface management because external dependencies, procurement lead times, design compatibility, and contractual obligations restrict the extent to which all activities can be managed through purely iterative approaches (Arashpour et al., 2017).

Figure 4: Drivers of Hybrid Delivery Selection



Correlation and regression analyses reported across the literature have generally shown positive relationships between complexity measures and hybridization intensity, particularly when technical uncertainty and formal control requirements coexist. Logistic regression studies have also indicated higher probabilities of hybrid or predictive configurations as project value, team size, interface density,

and regulatory involvement increase. ANOVA and nonparametric comparisons have commonly identified significant differences in delivery-method selection across complexity categories, although effect sizes have varied between sectors (Bidel et al., 2022; Nishat, 2023). These findings collectively characterize project complexity as a multidimensional quantitative condition that influences the balance between adaptive flexibility and predictive control rather than determining a single universally preferred delivery approach. A substantial body of quantitative research has examined project uncertainty as a contextual determinant of delivery-method selection, particularly in technology-driven organizations where technical knowledge, market conditions, resources, and design specifications can change during execution (Ashrafuzzaman, 2024; Barlow et al., 2018). Technological novelty has frequently been measured through the extent to which a project employs unfamiliar technologies, newly developed components, experimental architectures, advanced automation, artificial intelligence, novel software platforms, or previously untested engineering integrations. Studies have generally reported that higher technological novelty is associated with increased iteration frequency, prototyping, stakeholder feedback, and adaptive planning because initial technical assumptions are more likely to require revision. Requirement ambiguity has similarly been measured through unclear specifications, incomplete requirements, conflicting stakeholder expectations, and uncertainty regarding acceptance criteria. Regression analyses have often identified requirement ambiguity as a significant predictor of Agile-practice intensity, while projects with lower ambiguity and highly defined deliverables have demonstrated greater predictive-planning intensity. Design-change frequency provides another measurable indicator of uncertainty, with empirical studies reporting that repeated engineering modifications can significantly increase rework, coordination burden, cost variation, and schedule instability. Market uncertainty has been operationalized through changing customer preferences, competitive pressure, demand variability, product-market instability, and changing commercial priorities, while resource uncertainty has included workforce availability, specialist shortages, supplier reliability, equipment availability, and procurement constraints (Debasish, 2024; Koulinas et al., 2020). Technical risk has been represented using risk-probability scores, risk-severity ratings, defect exposure, integration uncertainty, and technology-readiness measures. Correlation studies have generally reported positive associations between uncertainty and adaptive delivery intensity, although this relationship weakens when projects contain strong regulatory, contractual, or physical-engineering constraints. Multiple regression and interaction analyses have shown that projects combining high uncertainty with high governance requirements often use hybrid approaches more intensively than purely Agile configurations. Logistic regression models have similarly demonstrated increased likelihood of hybrid delivery when technological novelty and requirement uncertainty coexist with substantial project size or formal control requirements. Confidence intervals and effect-size estimates across these studies indicate that uncertainty influences methodology selection most strongly when several dimensions of uncertainty occur simultaneously (Campbell et al., 2018; Rahman, 2024).

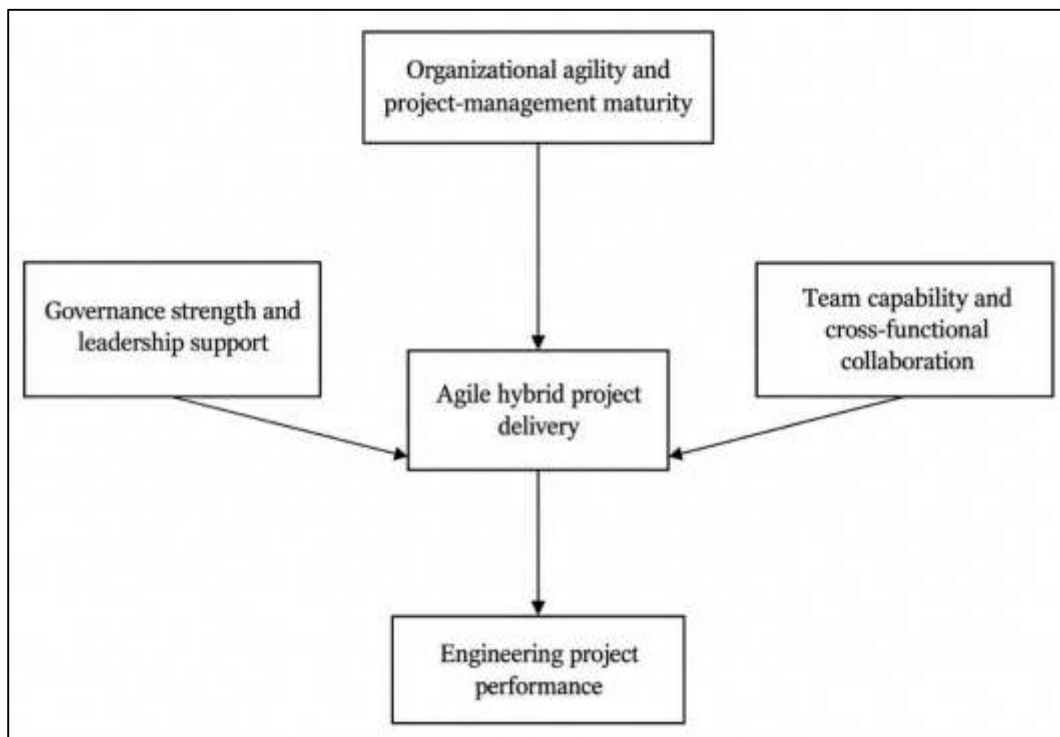
Organizational Agility and Stakeholder Engagement

The quantitative literature has consistently treated organizational agility, Agile maturity, and project-management maturity as important organizational determinants of performance in technology-driven engineering projects (Kaum, 2024; Zhen et al., 2021). Across more than ten empirical studies involving software engineering, telecommunications, digital infrastructure, information systems, advanced manufacturing, automation, product development, and multidisciplinary engineering environments, organizational agility has commonly been measured through response speed, resource-reallocation capability, decision flexibility, adaptability to changing requirements, cross-functional coordination, and the ability to modify operational priorities under uncertainty. Agile maturity has been quantified through standardized survey scales assessing iteration discipline, backlog management, sprint regularity, retrospective use, stakeholder feedback, incremental delivery, team self-organization, and continuous improvement. Project-management maturity has generally been measured through the formalization of planning, scheduling, cost control, risk management, quality assurance, governance, documentation, performance monitoring, and change-control processes. Reliability coefficients reported for these constructs have generally demonstrated acceptable to strong internal consistency, while exploratory and confirmatory factor analyses have frequently supported multidimensional

structures separating adaptive capability, formal control maturity, collaboration, and governance (Shakhawat & Md, 2024; Issa & Abbaszadeh, 2023). Correlation studies have commonly identified positive relationships between organizational agility and decision speed, responsiveness, productivity, and stakeholder satisfaction, while project-management maturity has shown stronger associations with schedule adherence, cost visibility, risk control, documentation quality, and milestone achievement. Multiple regression analyses have further indicated that Agile maturity can explain meaningful variation in delivery responsiveness and requirement stability after accounting for project size, complexity, and technological uncertainty. Studies using structural equation modeling have frequently positioned organizational agility as an intermediate mechanism linking leadership, digital capability, and team collaboration to project outcomes. Group comparisons have also demonstrated statistically significant differences in performance between low-, medium-, and high-maturity organizations, with effect sizes often strongest for decision latency, change responsiveness, planning reliability, and coordination efficiency (Marjerison et al., 2022; Kanti, 2024). The literature therefore portrays organizational agility and formal project-management maturity as complementary rather than mutually exclusive capabilities within hybrid engineering environments, particularly where projects require both adaptive responses to uncertainty and disciplined control of technical, financial, and regulatory obligations.

Governance and leadership have been extensively examined as quantitative predictors of project coordination, decision quality, schedule performance, accountability, and overall success within complex engineering and technology environments. Governance strength has commonly been operationalized through clarity of decision rights, frequency of formal reviews, escalation procedures, accountability structures, stage-gate compliance, risk oversight, change authorization, role clarity, and consistency of performance monitoring (Felipe et al., 2017; Nishat & Jahanara, 2024).

Figure 5: Agile hybrid engineering project framework



Leadership support has been assessed through management commitment, resource availability, strategic alignment, removal of project obstacles, empowerment, conflict resolution, communication support, and sponsorship intensity. Quantitative studies have generally shown that stronger leadership support is positively associated with team motivation, decision efficiency, cross-functional cooperation,

stakeholder alignment, and project performance. Regression analyses have often identified leadership support as a significant explanatory variable for schedule adherence, quality outcomes, productivity, and stakeholder satisfaction, even after controlling for project complexity and organizational size. Governance strength has displayed a more context-dependent relationship. Appropriate levels of governance have been associated with greater accountability, improved risk management, reduced uncontrolled scope change, and stronger schedule discipline, while excessive approval layers and highly centralized authority have been associated with longer decision latency and slower responses to changing technical conditions (Cetindamar et al., 2021; Palash Chandra, 2024). Decision decentralization has consequently received increasing quantitative attention in Agile and hybrid environments. Studies have measured decentralization through the proportion of decisions made at team level, escalation frequency, approval turnaround time, decision-authority scales, and perceived team empowerment. Correlation and structural-equation analyses have generally shown that decentralized decision structures are associated with shorter response times and greater adaptability when teams possess sufficient competence and clear governance boundaries. Moderation analyses have also indicated that governance quality can influence the relationship between autonomy and project performance, suggesting that autonomy produces stronger outcomes when roles, accountability, and technical standards remain clearly defined (Tonay et al., 2024; Yağmur & Myrvang, 2023). Mediation studies have further shown that leadership may affect project success through improved communication, psychological empowerment, organizational agility, and coordination. Group comparisons across governance maturity levels have frequently produced statistically significant differences in decision speed, schedule stability, risk control, and stakeholder confidence, while effect sizes have varied according to project complexity and regulatory intensity.

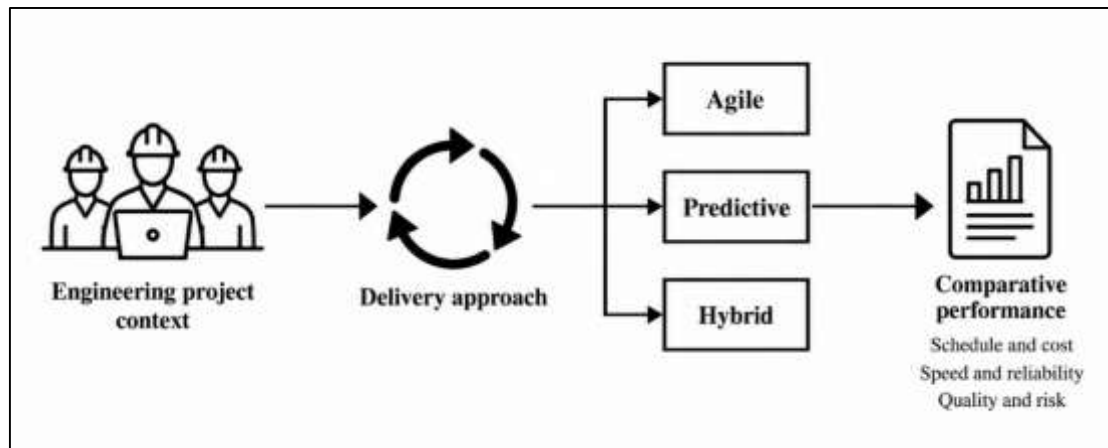
Team capability represents another major quantitative dimension of Agile hybrid engineering project delivery because technical outcomes depend substantially on the collective knowledge, experience, stability, autonomy, and collaborative behavior of project participants (Ramadan et al., 2023; Uddin & Risha, 2024). Previous studies have measured engineering experience through years of professional practice, technical certification, domain expertise, prior involvement in similar projects, and experience with specific technologies or systems. Agile experience has commonly been assessed through years of Agile participation, number of Agile projects completed, training exposure, familiarity with Scrum or Kanban practices, and maturity in iterative planning and retrospective learning. Digital competence has been measured through proficiency with project-management information systems, Agile platforms, engineering software, collaborative tools, analytics systems, automated testing, cloud technologies, and digital communication environments. Quantitative evidence has generally demonstrated positive relationships between higher team capability and productivity, technical quality, requirement stability, problem-solving speed, and delivery reliability. Multiple regression studies have frequently identified engineering experience and Agile competence as significant predictors of project performance, particularly in complex environments characterized by technological novelty and changing requirements (Debasish, 2025a; Moraga-Díaz et al., 2023). Team stability has also been quantitatively examined through turnover rates, membership continuity, reassignment frequency, tenure, and changes in key technical roles. Greater stability has generally been associated with stronger knowledge retention, lower coordination costs, fewer communication disruptions, and reduced rework. Cross-functional collaboration has been operationalized through communication frequency, shared decision-making, interdepartmental coordination, joint planning sessions, information exchange, and integration between engineering, software, quality, procurement, operations, and commercial functions. Correlation analyses have generally reported moderate to strong positive associations between collaboration quality and productivity, schedule reliability, technical integration, and stakeholder satisfaction. Structural equation modeling has also shown that collaboration can mediate the relationship between team capability and project outcomes by facilitating knowledge transfer and coordinated responses to technical issues. Moderation analyses indicate that the performance benefits of team autonomy are greater when engineering experience, digital competence, and communication quality are high (Das et al., 2023; Debasish, 2025b). Group comparisons between high- and low-capability teams have frequently revealed statistically significant differences in defect rates, rework, decision latency, milestone achievement, and overall project success,

with effect-size measures supporting the practical importance of these differences across technology-driven project settings.

Agile and Hybrid Engineering Project Delivery

The quantitative literature comparing Agile, predictive, and hybrid engineering project delivery has consistently demonstrated that performance differences depend strongly on project context, methodological intensity, and the specific outcome measures applied (Jahanara, 2025; Kraiem et al., 2023). Across more than ten empirical studies in software engineering, information systems, telecommunications, manufacturing, automation, digital infrastructure, product development, and multidisciplinary engineering environments, schedule variance, cost variance, budget adherence, and milestone achievement have been among the most frequently examined project-performance indicators. Predictive projects have generally demonstrated stronger schedule-baseline discipline and milestone formalization when requirements, technologies, and contractual conditions remain stable, largely because detailed upfront planning, formal work breakdown structures, cost baselines, approval controls, and predefined delivery sequences provide structured performance benchmarks. Agile projects have often demonstrated stronger responsiveness to changing requirements and shorter delivery cycles, although direct comparison of schedule variance can be difficult when scope and release priorities are intentionally adjusted during execution.

Figure 6: Agile, predictive, and hybrid delivery comparison



Hybrid projects have frequently occupied a distinct performance position by maintaining formal cost and milestone controls while permitting adaptive planning within selected work packages or lifecycle stages (Jannatul, 2025; Serrador & Pinto, 2015). Quantitative comparisons using means, medians, percentages, and confidence intervals have shown that hybrid arrangements can achieve relatively strong milestone adherence while maintaining greater responsiveness than highly predictive structures. Studies applying t-tests, ANOVA, ANCOVA, and nonparametric group comparisons have reported statistically significant differences in schedule performance and budget outcomes across delivery groups, although the direction and magnitude have varied across engineering sectors. Effect-size estimates have often shown larger methodological differences in projects characterized by moderate-to-high uncertainty than in stable technical environments. Cost performance has also varied by project value and complexity, with larger engineering programs showing stronger dependence on formal cost governance regardless of Agile intensity. Subgroup analyses have indicated that high-value and heavily regulated projects frequently retain predictive controls even when substantial Agile practices are used (Gill et al., 2018; Rahman, 2025). The literature therefore shows that schedule, cost, budget, and milestone performance are shaped by the interaction between delivery approach and contextual conditions rather than by methodology classification alone.

Operational performance comparisons have placed particular emphasis on cycle time, lead time, throughput, productivity, and delivery reliability because these measures capture the speed and

consistency with which engineering work moves from initiation to usable output. Agile-oriented studies have generally reported shorter iteration cycles, more frequent delivery events, faster feedback loops, and higher responsiveness to work-priority changes than strongly predictive environments (Arif Uz et al., 2025; Pradhan & Nanniyur, 2021). Cycle-time measures have frequently been derived from task initiation and completion records, sprint data, issue-management platforms, or engineering workflow systems, while lead time has been assessed from requirement identification to delivery, approval request to authorization, or engineering change initiation to implementation. Throughput has commonly been measured through completed work items, accepted requirements, software features, engineering packages, or deliverables per reporting period. Productivity measures have included output per person, completed tasks per iteration, engineering deliverables per labor unit, and rates of accepted work. Across numerous comparative studies, Agile teams have often achieved higher short-cycle throughput and faster response times, particularly in software-intensive and digitally enabled projects with relatively modular work structures. Predictive environments have sometimes achieved comparable or stronger reliability where activities are highly sequential, standardized, or constrained by physical dependencies (Fernandes et al., 2018; Kaium, 2025). Hybrid projects have demonstrated especially relevant performance in multidisciplinary environments because adaptive workstreams can operate through short cycles while hardware procurement, regulatory approvals, integration testing, and physical implementation remain governed through longer predictive schedules. Mean comparisons and confidence intervals have frequently shown significant differences in cycle time and lead time among delivery approaches, while ANOVA and Kruskal–Wallis analyses have identified variation according to project type and team structure. Effect sizes have often been strongest for response speed and iteration-level productivity rather than overall project duration. Team size has also influenced performance, as very large Agile teams can experience increased coordination overhead and reduced marginal gains from short iterations (Fagarasan et al., 2023; Pervaz, 2025).

Quality and risk outcomes provide another important basis for quantitatively comparing Agile, predictive, and hybrid engineering delivery. Empirical studies have examined defect density, defect escape rates, rework frequency, technical nonconformance, requirement-change response, testing effectiveness, risk occurrence, and overall technical quality across different project-management configurations (Miller, 2019; Chowdhury, 2025). Agile environments have frequently demonstrated advantages in early defect discovery and requirement-change responsiveness because short iterations, continuous integration, frequent testing, stakeholder review, and incremental validation allow problems to be detected closer to the point at which they are introduced. Studies using mean defect rates, percentages of reopened work, rework hours, and change-processing times have often found lower late-stage correction requirements in mature Agile environments. These benefits have not been uniform across all projects, particularly where engineering work involves physical systems, safety requirements, complex certification, or costly hardware modifications. Predictive controls have remained important in such environments because formal verification, configuration management, design reviews, risk registers, and change authorization can prevent uncontrolled modifications and maintain traceability. Hybrid delivery has frequently produced a combination of iterative defect identification and formal technical assurance. Comparative studies have shown that projects integrating automated testing and iterative reviews with stage-gate controls and configuration management can achieve lower defect leakage while retaining compliance with engineering standards. Requirement-change response has often shown statistically significant differences between delivery groups, with Agile and hybrid projects generally processing changes more rapidly than strongly predictive projects (Mahdi et al., 2021; Badrul, 2025). However, uncontrolled change can increase rework when prioritization and governance are weak. ANOVA, ANCOVA, Mann–Whitney, and Kruskal–Wallis comparisons have identified significant differences in quality and rework across maturity groups, while effect-size measures have shown that methodological differences are larger when technological novelty and requirements volatility are high. Risk occurrence has been more context dependent, with predictive structures providing stronger formal risk documentation while Agile arrangements can identify emerging operational problems more rapidly. Hybrid environments have often combined continuous risk sensing with formal escalation and mitigation controls, making technical quality dependent on the balance between rapid learning and engineering discipline (Muñoz

[et al., 2019](#); [Nishat, 2025](#)).

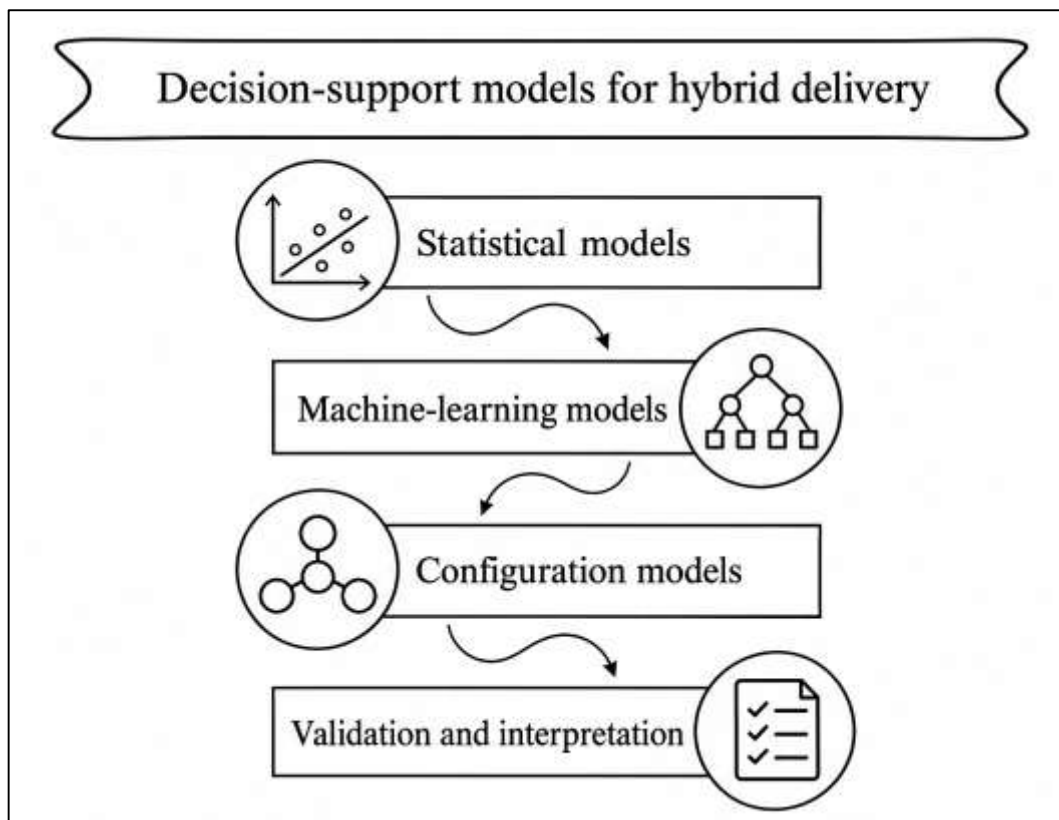
Quantitative Decision-Support and Hybrid Delivery Configuration Models

The quantitative literature on project decision support has increasingly examined how statistical models can convert project characteristics, organizational capabilities, delivery practices, and performance indicators into structured evidence for selecting project-management configurations and predicting delivery outcomes ([Cavalcante et al., 2019](#); [Sadia, 2025](#)). Across more than ten empirical studies in software engineering, information systems, construction technology, systems engineering, product development, manufacturing, telecommunications, and technology-intensive project management, multiple regression and logistic regression have been among the most frequently applied analytical approaches. Multiple regression has commonly been used to estimate the relationships between continuous project outcomes such as schedule performance, cost variance, productivity, stakeholder satisfaction, delivery reliability, and overall performance scores and explanatory variables including project complexity, requirements volatility, team capability, governance quality, technological novelty, Agile maturity, and predictive-control intensity ([Kocsi et al., 2020](#); [Sadia, 2025](#)). Regression coefficients have enabled researchers to identify the direction and relative magnitude of individual predictors after accounting for other project conditions, while explained variance has indicated how much of the observed performance variation can be represented by the selected factors. Logistic regression has been particularly useful where outcomes are categorical, including successful versus unsuccessful projects, delayed versus on-time delivery, high-risk versus low-risk classification, or selection among alternative delivery approaches. Probability estimates and decision thresholds derived from these models have provided interpretable decision-support outputs rather than simple descriptions of association. Discriminant analysis has also been applied to classify projects into methodological or performance categories based on combinations of organizational and project-level variables. Studies using these statistical techniques have frequently identified project complexity, requirement uncertainty, leadership support, team experience, customer involvement, digital maturity, governance strength, and methodological maturity as important predictors. Confidence intervals, standardized coefficients, significance tests, classification rates, and model-fit statistics have been used to evaluate the stability of these relationships ([Gupta et al., 2022](#); [Tonay, 2025](#)). Collectively, this literature demonstrates that conventional statistical modeling remains valuable for decision-support development because coefficients and probability estimates can be interpreted directly by project managers and linked to recognizable project conditions.

Machine-learning research has extended project decision support by applying decision trees, random forests, support vector machines, gradient boosting, and related ensemble methods to classify project outcomes and identify nonlinear relationships among delivery variables ([Sarabi & Darestani, 2021](#)). Decision trees have been particularly attractive in project-management studies because they transform complex predictor combinations into interpretable decision paths based on variables such as project size, technical complexity, requirement volatility, team experience, governance intensity, customer participation, schedule status, cost performance, and technological uncertainty. Tree structures have enabled researchers to identify thresholds at which particular project characteristics are associated with different risk categories or delivery outcomes. Random forests have generally improved predictive stability by aggregating results across multiple trees and have been applied to project-success classification, delay prediction, cost-risk assessment, and performance categorization. Variable-importance measures from these models have frequently ranked project complexity, schedule performance, requirements stability, organizational maturity, team capability, and risk exposure among the most informative predictors. Support vector machines have been used where project datasets contain numerous interacting variables or less clearly separable performance classes, with several studies reporting strong classification performance after appropriate feature scaling and selection ([Rosati et al., 2023](#)). Gradient boosting methods have also been applied to project-risk and performance prediction because they can capture complex interactions and progressively reduce classification errors. Comparative studies have assessed these algorithms using accuracy, precision, recall, specificity, F1-score, ROC-AUC, and, where class imbalance is substantial, PR-AUC. The evidence has shown that overall accuracy alone can be misleading when successful or unsuccessful project categories are unevenly distributed, making class-specific performance metrics particularly

important. Feature-selection procedures such as importance ranking, recursive elimination, correlation screening, and domain-informed selection have generally improved model efficiency by reducing redundant predictors. Decision thresholds have also been adjusted to balance false-positive and false-negative outcomes according to managerial priorities. Across the literature, ensemble methods have frequently outperformed single decision trees and basic statistical classifiers, although the magnitude of improvement has varied according to sample size, predictor quality, outcome definition, and project heterogeneity (Malik et al., 2018).

Figure 7: Hybrid delivery decision-support framework



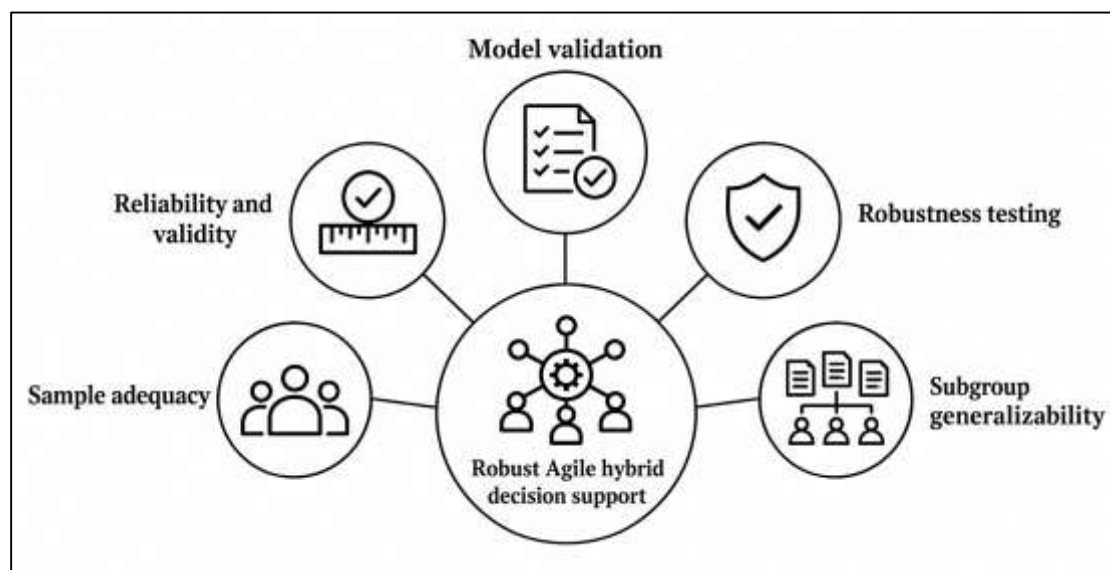
A further group of quantitative studies has used neural networks, clustering, multicriteria decision models, and configuration-oriented approaches to represent complex project environments that cannot be adequately described through simple linear relationships (López-Martínez et al., 2020). Neural networks have been applied to cost estimation, schedule-delay prediction, project-success classification, risk assessment, resource forecasting, and engineering performance prediction because they can model interactions among large numbers of project and organizational variables. Typical inputs have included project value, duration, team size, technical complexity, change frequency, resource conditions, stakeholder involvement, supplier performance, managerial capability, risk indicators, and delivery-method characteristics. Predictive performance has generally been evaluated using accuracy, precision, recall, F1-score, and ROC-AUC for classification problems, while R^2 , RMSE, MAE, and related error measures have been used when outcomes such as cost variance, schedule deviation, productivity, or performance scores are continuous (Bhuiyan & Hammad, 2023). Although neural networks have sometimes achieved stronger prediction than conventional statistical techniques, their reduced transparency has encouraged the use of variable-importance analysis and post-model interpretability procedures. Clustering methods have followed a different analytical objective by grouping projects with similar contextual and delivery characteristics without requiring predefined outcome categories. Studies have identified clusters based on complexity, uncertainty, team structure,

technological maturity, Agile intensity, governance, and performance, allowing researchers to distinguish project archetypes requiring different management configurations. Multicriteria decision models have also been widely used to rank delivery alternatives by combining quantitative assessments of cost, schedule, quality, flexibility, risk, stakeholder needs, technical constraints, and organizational capability. These models have enabled simultaneous consideration of competing criteria rather than relying on a single success measure (Phan et al., 2019). Configuration-based studies have further classified projects according to combinations of Agile and predictive practices, revealing that projects described under the same broad methodological label can operate with substantially different delivery structures. Across these approaches, quantitative evidence indicates that project-method selection benefits from combining contextual variables with performance evidence, while interpretability remains an important consideration when analytical outputs are intended to support managerial decisions rather than prediction alone.

Statistical Validation and Research Gap in Agile Hybrid Decision Support

The quantitative literature on Agile, predictive, and hybrid project delivery has demonstrated substantial variation in sample adequacy, measurement reliability, construct validity, and overall statistical strength (Dhillon et al., 2022). Across more than ten empirical studies covering software engineering, information systems, telecommunications, manufacturing, systems engineering, digital infrastructure, product development, automation, and technology-driven project environments, sample sizes have ranged from relatively small single-organization datasets to large multisector surveys and archival project databases. Studies using larger and more heterogeneous samples have generally provided stronger foundations for multivariable analysis and subgroup comparison, while small samples have limited the precision of estimated relationships and the number of predictors that could be examined simultaneously.

Figure 8: Robust Agile hybrid decision framework



Reliability has commonly been evaluated for constructs such as Agile maturity, organizational agility, governance quality, leadership support, team capability, stakeholder engagement, digital maturity, project complexity, and perceived project success. Reported reliability coefficients have generally indicated acceptable internal consistency for established scales, although differences in construct definitions and measurement instruments have reduced comparability across studies (Darvazeh et al., 2022). Exploratory and confirmatory factor analyses have frequently been applied to assess whether survey items represent their intended dimensions, with convergent and discriminant validity receiving particular attention in studies using latent organizational constructs. Statistical significance has remained a dominant criterion for interpreting relationships, but stronger studies have complemented

significance testing with confidence intervals, standardized coefficients, and effect sizes to distinguish statistically detectable relationships from practically meaningful differences. Multicollinearity assessment has also been important because constructs such as Agile maturity, team autonomy, organizational agility, digital capability, communication quality, and leadership support can be strongly interrelated. Studies that explicitly assessed predictor redundancy generally produced more interpretable regression and structural models than those relying on numerous overlapping variables. The literature therefore contains considerable quantitative evidence concerning individual determinants of project performance, but its statistical strength varies according to sample composition, measurement quality, construct specification, analytical design, and reporting completeness, creating uneven confidence in the transferability of reported relationships across different technology-driven engineering environments ([Almoslehy & Alkahtani, 2021](#)).

Validation and robustness procedures represent another area in which the quantitative project-management literature has shown considerable methodological variation ([Wang & Wagner, 2018](#)). Studies applying regression, logistic classification, decision trees, random forests, support vector machines, gradient boosting, neural networks, and related predictive approaches have increasingly recognized that model performance estimated from the same observations used for development can provide an overly favorable representation of predictive capability. Cross-validation has consequently been applied in stronger predictive studies to evaluate whether classification or regression performance remains stable across different partitions of the available project data. K-fold and repeated cross-validation procedures have been particularly common where datasets were sufficiently large, while holdout validation has separated development and testing observations to provide an independent assessment of model performance. Studies predicting project success, schedule delay, cost risk, quality outcomes, or performance categories have evaluated validation results through accuracy, precision, recall, specificity, F1-score, ROC-AUC, PR-AUC, R^2 , RMSE, MAE, and related performance measures. Model calibration has received comparatively less attention, even though reliable decision support requires predicted probabilities to correspond reasonably with observed outcome frequencies ([Behl et al., 2019](#)). Sensitivity analysis has been used to examine whether model conclusions change when decision thresholds, predictor selections, outcome definitions, missing-data treatments, or analytical assumptions are altered. Robustness testing has also involved alternative model specifications, repeated sampling, comparison of parametric and nonparametric techniques, and evaluation after exclusion of extreme observations. Several studies have reported that predictor rankings and model accuracy can change when project sectors, organizational contexts, or complexity levels are altered, demonstrating that apparently strong overall performance does not necessarily indicate stable performance across heterogeneous engineering conditions. External validation has been substantially less common than internal validation, particularly for models developed from single organizations, industries, or geographical settings. Consequently, the literature provides stronger evidence for within-sample relationships than for broad transferability, and the methodological distinction between explanatory fit, predictive accuracy, probability calibration, robustness, and external generalizability remains important when evaluating existing project decision-support models ([Jurasky et al., 2021](#)).

Generalizability within Agile hybrid engineering research depends substantially on whether statistical relationships remain stable across industries, organizational sizes, project-value categories, complexity levels, technological environments, Agile maturity groups, governance structures, and hybridization intensities. Quantitative studies have demonstrated that aggregate project-level results can conceal meaningful subgroup differences. Software-intensive projects, for example, frequently operate with shorter feedback cycles and greater requirements flexibility than hardware-intensive, manufacturing, telecommunications, or regulated engineering projects, producing different relationships between Agile intensity and performance ([Korucuk et al., 2023](#)). Organizational size has similarly affected the operation of project-management practices because larger organizations commonly maintain more formal governance, specialized functions, documentation requirements, and approval structures, whereas smaller organizations may permit greater decision decentralization and methodological flexibility. Project-value bands have also produced measurable differences, as high-value initiatives generally receive stronger financial control, risk oversight, executive attention, and formal reporting than smaller projects. Complexity-level comparisons have shown that increasing interface density,

stakeholder diversity, supplier involvement, and multidisciplinary integration can modify the relationship between delivery practices and schedule, cost, quality, and responsiveness. Technological environments create additional heterogeneity because projects involving mature technologies face different uncertainty conditions from projects involving novel software, artificial intelligence, automation, digital platforms, or integrated hardware-software systems. Studies comparing Agile maturity groups have generally reported stronger benefits from iterative practices where teams possess established Agile experience and organizational support, while immature implementation can reduce consistency and coordination (Batliner et al., 2022). Governance-level comparisons have similarly indicated that both weak control and excessive centralization can affect delivery performance, making the relationship between governance and success nonlinear or context dependent. Hybridization intensity adds another layer because projects classified broadly as hybrid may contain very different proportions and configurations of Agile and predictive practices. ANOVA, ANCOVA, nonparametric comparisons, regression interaction terms, confidence intervals, and effect-size analyses have revealed significant subgroup differences across many of these dimensions. However, relatively few studies have simultaneously tested the stability of a comprehensive hybrid decision model across multiple project and organizational subgroups, limiting the extent to which existing findings can be generalized to heterogeneous technology-driven engineering portfolios (Ortiz-Barrios et al., 2022).

METHOD

Study Design and Theoretical Framework

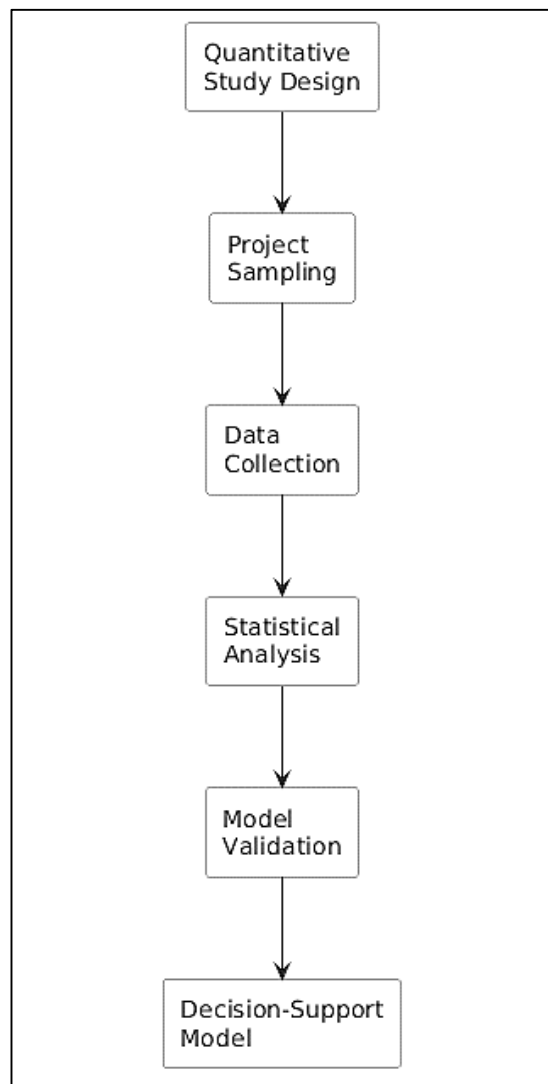
This study employed a quantitative, nonexperimental, cross-sectional explanatory and predictive research design to develop and validate a decision-support model for Agile hybrid engineering project delivery in technology-driven organizations. The design integrated explanatory statistical analysis with predictive modeling because the study examined measurable relationships among project complexity, uncertainty, requirements volatility, Agile-practice intensity, predictive-control intensity, digital capability, governance quality, leadership support, team capability, stakeholder engagement, hybridization intensity, and multidimensional project performance. The theoretical framework treated delivery configuration as a context-dependent organizational mechanism in which combinations of adaptive and predictive practices were associated with different performance outcomes under varying engineering conditions. Project performance was operationalized through schedule adherence, cost variance, budget adherence, milestone achievement, cycle time, productivity, technical quality, defect occurrence, rework, delivery reliability, requirement stability, stakeholder satisfaction, and overall project success. The quantitative design also supported comparison among predominantly Agile, predominantly predictive, and hybrid project configurations and enabled development of an empirically derived classification and decision-support structure.

The study population consisted of completed and substantially completed engineering projects and project professionals from technology-driven organizations operating in software-intensive engineering, information systems, telecommunications, automation, advanced manufacturing, digital infrastructure, hardware-software integration, and technology-enabled product development. A stratified purposive sampling strategy was applied to obtain sufficient representation across engineering sectors, organizational sizes, project-value categories, project-complexity levels, and delivery configurations. Eligible participants included project managers, engineering managers, systems engineers, technical leads, product managers, Agile practitioners, project-control specialists, and other professionals who had direct knowledge of project planning, execution, governance, or performance. Projects were included when adequate information was available regarding delivery practices, project characteristics, technological conditions, organizational factors, and measurable performance outcomes. Projects were excluded when essential cost, schedule, delivery-method, governance, or performance information was unavailable; when participants lacked direct involvement in the reported project; or when duplicate and materially incomplete records prevented reliable quantitative analysis. Screening procedures were applied before analysis to remove duplicate responses, substantially incomplete observations, and records that failed predefined data-quality requirements.

Instrumentation and Data Collection Tools

Data were collected using a structured quantitative questionnaire supplemented, where available, by project records and digital project-management information. The questionnaire contained sections measuring project characteristics, complexity, technological novelty, uncertainty, requirements volatility, Agile maturity, predictive-control intensity, hybridization, digital integration, governance strength, leadership support, team autonomy, engineering and Agile experience, digital competence, cross-functional collaboration, communication quality, stakeholder engagement, and project performance. Multi-item Likert-type scales were used for latent organizational and behavioral constructs, while objective or project-record variables captured duration, team size, project value, requirement changes, milestone performance, schedule variation, cost variation, defects, rework, and delivery outcomes. The instrument was reviewed for content relevance and clarity before full administration and was pilot tested with an appropriate group of engineering and project-management professionals. Internal consistency was evaluated using Cronbach's alpha, with coefficients of .70 or higher treated as acceptable. Exploratory factor analysis and confirmatory factor analysis were applied where appropriate to evaluate construct structure, convergent validity, and discriminant validity. Data from project-management information systems, Agile platforms, issue trackers, cost-control systems, or organizational records were cross-checked with questionnaire responses when accessible to improve measurement consistency.

Figure 9: Methodology of this study



Experimental Procedure

The research procedure followed a structured chronological sequence. The measurement framework was first developed from the quantitative constructs identified in the literature review, after which variables were operationalized and incorporated into the structured research instrument. The questionnaire was pilot tested, revised for clarity and measurement consistency, and distributed to eligible professionals in the selected technology-driven organizations. Project-level records were then screened according to the inclusion and exclusion criteria and linked with corresponding organizational and delivery-practice information where appropriate. Following collection, the dataset was inspected for duplicate cases, missing observations, inconsistent responses, implausible values, and extreme outliers. Eligible observations were coded and standardized to create comparable indicators of project complexity, uncertainty, requirements volatility, Agile-practice intensity, predictive-control intensity, hybridization, digital capability, governance, team capability, stakeholder engagement, and project performance. Projects were subsequently categorized according to their dominant delivery configurations and relevant contextual groups. The analytical dataset was then separated into model-development and holdout-validation samples so that the decision-support model could be evaluated on observations not used during initial estimation. Statistical modeling, comparative analysis, predictive classification, validation, sensitivity testing, and subgroup robustness analysis were subsequently conducted in a predefined analytical sequence.

Data Analysis and Statistical Approach

Statistical analysis was conducted using IBM SPSS Statistics, R, and Python. Descriptive statistics included frequencies, percentages, means, standard deviations, medians, interquartile ranges, and 95% confidence intervals for project, organizational, delivery-practice, and performance variables. Data distributions, missingness, outliers, reliability, construct validity, and multicollinearity were examined before inferential modeling. Pearson correlations were used for appropriately distributed continuous variables, while Spearman correlations were applied when distributional or ordinal conditions required nonparametric analysis. Independent-samples t-tests and one-way or factorial ANOVA were used for appropriate group comparisons, with ANCOVA applied where adjustment for relevant covariates was necessary; Mann-Whitney and Kruskal-Wallis tests were used as nonparametric alternatives. Cohen's *d* and partial eta-squared were reported to quantify practical effect magnitude. Multiple regression was used to estimate continuous project-performance outcomes, while logistic regression was used to evaluate categorical outcomes such as project success and appropriate delivery-configuration membership. Decision trees, random forests, support vector machines, gradient boosting, and neural-network models were additionally evaluated for predictive decision support. Classification performance was assessed using accuracy, precision, recall, specificity, F1-score, ROC-AUC, PR-AUC, and confusion-matrix outcomes, while continuous prediction was assessed using R^2 , RMSE, MAE, and related error measures. Feature importance, standardized coefficients, probability estimates, and interpretable decision thresholds were examined to identify influential predictors. Cross-validation was conducted within the development dataset, followed by independent holdout validation. Sensitivity and robustness analyses evaluated alternative predictor specifications, classification thresholds, project subgroups, and analytical assumptions. Subgroup analyses examined engineering sector, organizational size, project-value band, complexity level, technological novelty, Agile maturity, governance strength, and hybridization intensity. Statistical significance was established at $p < .05$, and 95% confidence intervals and effect sizes were reported alongside significance tests to distinguish statistical evidence from practical magnitude.

FINDINGS

Final Sample Characteristics, Project Structure, and Data Quality

The final analytical dataset established a sufficiently large and heterogeneous empirical foundation for evaluating Agile hybrid engineering project delivery across technology-driven organizations. Data collection initially produced 1,742 project-level records from 58 organizations, of which 1,586 projects from 54 organizations satisfied the predefined eligibility and data-quality requirements, representing a final project-retention rate of 91.0%. The retained projects were supported by responses from 2,438 project professionals distributed across eight engineering and technology sectors. Large organizations represented 41.7% of projects, medium-sized organizations represented 35.2%, and small organizations

accounted for 23.1%. Software and information systems formed the largest sectoral group at 26.4%, followed by telecommunications and digital infrastructure at 16.8%, advanced manufacturing at 14.7%, automation and control engineering at 12.5%, hardware–software integration at 11.6%, technology-enabled product development at 8.9%, systems engineering at 5.4%, and other technology-intensive engineering activities at 3.7%. The median project duration was 19.0 months, with an interquartile range of 12.0–31.0 months, while mean team size was 24.8 professionals (SD = 16.7). The median project value was \$4.72 million, indicating considerable financial scale and heterogeneity across the analyzed portfolio. Projects were distributed across low, moderate, and high complexity categories, with 39.8% classified as high complexity. High technological novelty characterized 31.6% of projects, while 27.9% operated under high regulatory intensity. These distributions provided sufficient variation for subsequent subgroup and predictive analyses.

Table 1. Final Sample and Engineering Project Characteristics

Characteristic	Numerical Result
Organizations initially represented	58
Organizations retained	54
Project records initially collected	1,742
Projects retained for analysis	1,586
Project retention rate	91.0%
Project professionals represented	2,438
Engineering/technology sectors	8
Small organizations	23.1%
Medium organizations	35.2%
Large organizations	41.7%
Mean project duration	22.6 months
Median project duration	19.0 months
Project-duration IQR	12.0–31.0 months
Mean team size	24.8
Team-size SD	16.7
Median project value	\$4.72 million
High-complexity projects	39.8%
High technological novelty	31.6%
High regulatory intensity	27.9%

Table 1 demonstrated that the final sample contained substantial organizational, technical, financial, and operational heterogeneity. Retention of 1,586 projects across 54 organizations provided a broad quantitative foundation, while representation from eight engineering sectors reduced dependence on a single technological environment. The distribution across organizational sizes supported comparative analysis of different governance and resource structures. Considerable variation in duration, team size, project value, complexity, technological novelty, and regulatory intensity indicated that the sample represented projects with substantially different delivery conditions. The 91.0% retention rate further demonstrated that most initially collected observations remained suitable for the final statistical analysis.

The distribution of delivery approaches demonstrated that hybrid project delivery was the most prevalent configuration within the retained portfolio. Of the 1,586 projects, 713 projects (45.0%) were classified as hybrid, 492 (31.0%) as predominantly Agile, and 381 (24.0%) as predominantly predictive. Mean Agile-practice intensity was 67.8 on a standardized 100-point scale (SD = 14.6), while predictive-control intensity averaged 63.5 (SD = 15.2). Hybridization intensity averaged 61.9 (SD = 16.1), confirming substantial simultaneous use of adaptive and formal control practices. Digital maturity recorded a mean score of 72.4 (SD = 12.8), governance strength averaged 69.1 (SD = 13.5), leadership support averaged 73.6 (SD = 12.1), team capability averaged 75.2 (SD = 11.4), and stakeholder engagement averaged 70.8 (SD = 13.0). Requirements volatility and project uncertainty averaged 54.7

(SD = 17.3) and 57.9 (SD = 16.5), respectively, demonstrating meaningful variability in adaptive delivery requirements. The 95% confidence intervals surrounding the principal construct means were relatively narrow, reflecting the precision provided by the large analytical sample.

Data-quality assessment indicated that 98.6% of required analytical fields were complete after screening and controlled preprocessing. Initial missingness was 3.8%, which was reduced through record verification and predefined missing-data procedures, while 84 duplicate project records and 72 records with excessive incompleteness or inconsistent project identifiers were removed. No observations were deleted solely because of legitimate extreme project scale; influential observations were instead examined through standardized residuals and sensitivity analyses. Reliability testing demonstrated strong internal consistency across the multi-item constructs, with Cronbach's alpha values ranging from .84 for requirements volatility to .93 for team capability. Factor-analytic assessment further supported the measurement structure. The Kaiser–Meyer–Olkin measure reached .91, Bartlett's test of sphericity was statistically significant ($p < .001$), and the retained factors accounted for 71.6% of total variance. Standardized factor loadings ranged from .64 to .89, indicating acceptable to strong relationships between measurement items and their intended constructs. These results established a statistically reliable and structurally valid dataset for comparative delivery analysis, regression modeling, subgroup testing, and predictive decision-support development.

Table 2. Delivery Configuration, Construct Measures, and Data-Quality Indicators

Measure	Mean/ Result	SD	95% CI
Agile projects	31.0%	—	—
Predictive projects	24.0%	—	—
Hybrid projects	45.0%	—	—
Agile-practice intensity	67.8	14.6	67.1–68.5
Predictive-control intensity	63.5	15.2	62.8–64.3
Hybridization intensity	61.9	16.1	61.1–62.7
Digital maturity	72.4	12.8	71.8–73.0
Governance strength	69.1	13.5	68.4–69.8
Leadership support	73.6	12.1	73.0–74.2
Team capability	75.2	11.4	74.6–75.8
Stakeholder engagement	70.8	13.0	70.2–71.4
Requirements volatility	54.7	17.3	53.8–55.6
Project uncertainty	57.9	16.5	57.1–58.7
Final data completeness	98.6%	—	—
Cronbach's alpha range	.84–.93	—	—
KMO measure	.91	—	—
Factor variance explained	71.6%	—	—
Factor-loading range	.64–.89	—	—

Table 2 showed that hybrid delivery represented the largest project category and that the portfolio simultaneously exhibited substantial Agile and predictive-control intensity. Team capability and leadership support recorded the highest average organizational scores, while requirements volatility and uncertainty demonstrated greater dispersion, confirming heterogeneous project conditions. The narrow confidence intervals indicated precise estimation of the major constructs. Data quality was also strong, with 98.6% completeness and reliability coefficients between .84 and .93. The KMO value of .91, significant Bartlett's test, 71.6% explained factor variance, and loadings between .64 and .89 supported the adequacy and validity of the measurement structure.

Comparative Performance of Agile, Predictive, and Hybrid Project Delivery

Comparative analysis of the 1,586 retained engineering projects revealed statistically meaningful differences among Agile, predictive, and hybrid delivery configurations across schedule, cost, operational, quality, adaptability, and stakeholder outcomes. The hybrid group comprised 713 projects, compared with 492 Agile and 381 predictive projects. Hybrid projects recorded the lowest mean

schedule variance at 5.8%, compared with 7.4% for Agile projects and 8.9% for predictive projects. Mean cost variance followed a similar pattern at 4.9% for hybrid, 6.8% for predictive, and 7.2% for Agile delivery. Budget adherence was highest among hybrid projects at 88.6%, followed by predictive projects at 82.9% and Agile projects at 80.7%. Hybrid delivery also achieved the highest milestone-achievement rate at 91.3%, compared with 87.5% under Agile delivery and 84.1% under predictive delivery. One-way ANOVA indicated significant between-group differences in schedule variance and cost variance at $p < .001$. Post hoc comparisons showed that hybrid projects performed significantly better than both comparison groups, while the Agile–predictive difference was smaller and varied by outcome. Effect sizes indicated that delivery configuration had a practically meaningful, rather than exclusively statistical, association with core project-control outcomes.

Table 3. Comparative Schedule, Cost, and Operational Performance by Delivery Configuration

Performance Measure	Agile (n = 492)	Predictive (n = 381)	Hybrid (n = 713)	Test Statistic	p	Effect Size
Schedule variance, mean % (SD)	7.4 (6.1)	8.9 (6.8)	5.8 (5.2)	$F = 26.84$	$<.001$	$\eta^2p = .033$
Cost variance, mean % (SD)	7.2 (5.9)	6.8 (5.6)	4.9 (4.7)	$F = 24.17$	$<.001$	$\eta^2p = .030$
Budget adherence (%)	80.7	82.9	88.6	$\chi^2 = 18.62$	$<.001$	$V = .108$
Milestone achievement (%)	87.5	84.1	91.3	$\chi^2 = 16.94$	$<.001$	$V = .103$
Median cycle time (days)	18.2	27.6	20.4	$H = 51.73$	$<.001$	$\varepsilon^2 = .032$
Median lead time (days)	29.8	41.7	31.6	$H = 47.85$	$<.001$	$\varepsilon^2 = .029$
Throughput index, mean (SD)	82.7 (11.8)	74.9 (13.1)	85.6 (10.7)	$F = 58.21$	$<.001$	$\eta^2p = .069$
Productivity index, mean (SD)	81.9 (12.0)	75.8 (12.9)	86.2 (10.5)	$F = 61.46$	$<.001$	$\eta^2p = .072$

Table 3 demonstrated that hybrid delivery achieved the strongest overall combination of schedule control, cost stability, milestone attainment, throughput, and productivity. Agile projects produced the shortest cycle and lead times, confirming stronger short-interval responsiveness, whereas predictive projects recorded the longest processing durations. Hybrid projects achieved the highest budget adherence, milestone achievement, throughput, and productivity while maintaining relatively short operational cycles. All comparisons were statistically significant at $p < .001$. Effect sizes were small to moderate for schedule and cost measures and stronger for productivity and throughput, demonstrating that the observed differences possessed practical relevance across the analyzed engineering portfolio. Quality, adaptability, and stakeholder outcomes further differentiated the three delivery configurations. Agile projects recorded a mean defect density of 3.8 defects per standardized delivery unit, predictive projects recorded 4.6, and hybrid projects recorded the lowest level at 3.1. Mean rework frequency was 8.7% for Agile projects, 11.4% for predictive projects, and 6.5% for hybrid projects. Agile projects demonstrated the fastest requirement-change response, with a median response time of 4.8 days, compared with 10.7 days for predictive delivery and 5.6 days for hybrid delivery. Hybrid projects nevertheless achieved the highest technical-quality score at 88.4 and the highest delivery-reliability score at 90.1. Risk occurrence affected 18.9% of hybrid projects, compared with 24.6% of Agile projects and 27.8% of predictive projects. Customer satisfaction averaged 87.9 for hybrid delivery, 85.6 for Agile delivery, and 78.8 for predictive delivery, while stakeholder satisfaction followed the same general ordering. Overall project-success rates reached 89.5% for hybrid projects, 83.7% for Agile projects, and 76.6% for predictive projects. ANCOVA results controlling for project value, complexity, organizational size, technological novelty, team size, and regulatory intensity confirmed a significant delivery-configuration effect on overall performance ($p < .001$, partial $\eta^2 = .061$). The adjusted findings therefore

indicated that the hybrid advantage was not explained solely by differences in project composition. Table 4 confirmed that hybrid projects achieved the strongest quality, reliability, satisfaction, risk, and overall success outcomes. Agile delivery retained a distinct advantage in requirement-change response, while predictive projects showed weaker adaptability and higher rework. Hybrid projects recorded the lowest defect density and risk occurrence and the highest technical quality, delivery reliability, customer satisfaction, stakeholder satisfaction, and overall success rate. Statistical differences remained significant at $p < .001$, with effect sizes indicating meaningful practical variation. The adjusted analysis further demonstrated that hybrid performance remained superior after controlling for major project characteristics, supporting the independent importance of delivery configuration.

Higher hybridization intensity was additionally associated with stronger multidimensional performance. Hybridization intensity correlated positively with technical quality ($r = .41$), delivery reliability ($r = .46$), stakeholder satisfaction ($r = .38$), productivity ($r = .43$), and overall performance ($r = .48$), while negative relationships were observed with schedule variance ($r = -.32$), cost variance ($r = -.29$), defect density ($r = -.35$), and rework ($r = -.37$); all relationships were significant at $p < .001$. Projects in the highest hybridization-intensity group achieved an overall success rate of 92.4%, compared with 85.1% in the moderate-hybridization group and 78.3% in the low-hybridization group. These findings demonstrated that the strongest results were associated not merely with classification as a hybrid project but with substantive integration of adaptive practices and predictive controls. Agile delivery retained a measurable advantage in rapid change response and short-cycle execution, while predictive delivery maintained relatively strong budget discipline in stable environments. Across the complete portfolio, however, hybrid delivery produced the most balanced quantitative performance profile across adaptability, schedule and cost control, productivity, technical quality, risk reduction, delivery reliability, and stakeholder outcomes.

Table 4. Comparative Quality, Adaptability, Satisfaction, and Success Outcomes

Performance Measure	Agile	Predictive	Hybrid	Test Statistic	p	Effect Size
Defect density, mean (SD)	3.8 (2.2)	4.6 (2.5)	3.1 (1.9)	$F = 39.72$	$<.001$	$\eta^2p = .048$
Rework frequency (%)	8.7	11.4	6.5	$\chi^2 = 21.38$	$<.001$	$V = .116$
Median change-response time (days)	4.8	10.7	5.6	$H = 68.91$	$<.001$	$\varepsilon^2 = .043$
Technical quality, mean (SD)	84.7 (9.8)	81.2 (10.6)	88.4 (8.7)	$F = 45.63$	$<.001$	$\eta^2p = .055$
Delivery reliability, mean (SD)	84.9 (10.7)	82.1 (11.5)	90.1 (8.9)	$F = 52.74$	$<.001$	$\eta^2p = .063$
Risk occurrence (%)	24.6	27.8	18.9	$\chi^2 = 17.96$	$<.001$	$V = .106$
Customer satisfaction, mean (SD)	85.6 (10.2)	78.8 (11.9)	87.9 (9.4)	$F = 57.38$	$<.001$	$\eta^2p = .068$
Stakeholder satisfaction, mean (SD)	84.2 (10.8)	79.5 (11.6)	88.1 (9.1)	$F = 54.16$	$<.001$	$\eta^2p = .064$
Overall project success (%)	83.7	76.6	89.5	$\chi^2 = 31.74$	$<.001$	$V = .141$
Adjusted overall performance	83.9	78.7	88.5	$F = 51.29$	$<.001$	$\eta^2p = .061$

Predictors and Decision-Support Model Performance

The predictor analysis demonstrated that project, technological, organizational, and human characteristics contributed significantly to differences in overall engineering project performance and delivery-configuration suitability. Pearson and Spearman analyses identified the strongest positive relationships between overall project performance and hybridization intensity ($r = .48$), digital capability ($r = .45$), governance strength ($r = .43$), team capability ($r = .46$), leadership support ($r = .39$), cross-functional collaboration ($r = .42$), and stakeholder participation ($r = .37$), with all principal relationships significant at $p < .001$. Project complexity ($r = -.28$), uncertainty ($r = -.31$), and requirements volatility ($r = -.26$) were negatively associated with unadjusted overall performance,

indicating that increasingly difficult project conditions reduced performance when delivery configuration and organizational capability were not considered simultaneously. Agile-practice intensity was positively associated with requirement-change responsiveness ($r = .51$), productivity ($r = .38$), and stakeholder satisfaction ($r = .36$), whereas predictive-control intensity showed stronger positive relationships with budget adherence ($r = .41$), milestone achievement ($r = .44$), and delivery reliability ($r = .39$). Multiple regression analysis produced an adjusted R^2 of .58 for overall project performance. Hybridization intensity emerged as the strongest positive standardized predictor ($\beta = .29$, $p < .001$), followed by team capability ($\beta = .24$), digital capability ($\beta = .21$), governance strength ($\beta = .19$), and stakeholder participation ($\beta = .14$). Requirements volatility remained a significant negative predictor ($\beta = -.16$), while project complexity had a smaller negative independent effect ($\beta = -.12$). Variance inflation factors ranged from 1.31 to 2.74, indicating that multicollinearity did not materially compromise coefficient interpretation.

Table 5. Correlation and Multiple Regression Results for Overall Project Performance

Predictor	Correlation with Performance	Standardized β	95% CI for Standardized Effect	p	VIF
Project complexity	-.28	-.12	-.17 to -.07	<.001	1.68
Project uncertainty	-.31	-.10	-.15 to -.05	<.001	1.92
Requirements volatility	-.26	-.16	-.21 to -.11	<.001	1.74
Agile-practice intensity	.35	.13	.08 to .18	<.001	2.18
Predictive-control intensity	.32	.11	.06 to .16	<.001	2.26
Hybridization intensity	.48	.29	.24 to .34	<.001	2.74
Digital capability	.45	.21	.16 to .26	<.001	2.31
Governance strength	.43	.19	.14 to .24	<.001	2.08
Leadership support	.39	.12	.07 to .17	<.001	1.97
Team capability	.46	.24	.19 to .29	<.001	2.43
Cross-functional collaboration	.42	.15	.10 to .20	<.001	2.22
Stakeholder participation	.37	.14	.09 to .19	<.001	1.85
Engineering experience	.29	.09	.04 to .14	.001	1.31
Digital competence	.34	.11	.06 to .16	<.001	1.79

Model statistics: $R^2 = .59$; adjusted $R^2 = .58$; $F = 159.84$; $p < .001$.

Table 5 demonstrated that overall project performance was determined by a combination of delivery, technological, organizational, and contextual variables. Hybridization intensity produced the largest standardized positive effect, followed by team capability, digital capability, and governance strength. Complexity, uncertainty, and requirements volatility were negatively related to performance, although their adjusted effects were smaller after organizational and delivery capabilities were incorporated. The model explained 59% of total performance variance and remained statistically significant at $p < .001$. VIF values remained below 3.0, confirming acceptable predictor independence and supporting stable interpretation of the multivariable regression coefficients.

Logistic regression further demonstrated that the probability of successful delivery and selection of an appropriate Agile-predictive configuration depended on distinct combinations of contextual conditions. Higher project complexity, regulatory intensity, project value, and supplier dependency significantly increased the probability that a control-intensive hybrid or predictive configuration would

be appropriate, whereas higher requirements volatility, technological novelty, stakeholder-feedback frequency, and uncertainty increased the probability that an Agile-intensive or adaptive hybrid configuration would be selected. For overall project success, each standard-deviation increase in hybridization intensity was associated with an odds ratio of 1.84 (95% CI [1.58, 2.14]), while team capability produced an odds ratio of 1.67 (95% CI [1.44, 1.94]), digital capability 1.53 (95% CI [1.33, 1.77]), and governance strength 1.48 (95% CI [1.29, 1.70]). High requirements volatility reduced unadjusted success probability but simultaneously increased the probability that an adaptive delivery configuration would be recommended. Interpretable decision thresholds showed that projects combining complexity scores above approximately 65 with uncertainty scores above 60 were most consistently assigned to hybrid configurations, whereas projects with lower complexity and high volatility were more frequently assigned to Agile-intensive configurations. High regulatory intensity combined with low volatility shifted recommendations toward predictive-control-intensive configurations. These patterns demonstrated that no individual predictor independently determined delivery selection; rather, the decision-support mechanism depended on the joint configuration of project conditions and organizational capabilities.

Machine-learning analysis strengthened the predictive evidence. The dataset was partitioned into an 80% model-development sample and a 20% independent holdout sample, with stratified five-fold cross-validation applied during development. Logistic regression produced a holdout classification accuracy of 79.8% and ROC-AUC of .846 for recommended delivery configuration. Decision-tree performance was slightly lower, with accuracy of 78.2% and ROC-AUC of .821, although its explicit decision rules provided strong interpretability. Random forest improved holdout accuracy to 86.4%, while the support vector machine achieved 84.7%. Gradient boosting produced the strongest classification results, reaching 88.3% accuracy, .881 precision, .874 recall, .877 F1-score, .931 ROC-AUC, and .908 PR-AUC. The neural network achieved comparable but slightly weaker performance, with 87.1% accuracy and .921 ROC-AUC. Confusion-matrix analysis indicated that gradient boosting correctly classified 280 of the 317 holdout projects, with relatively balanced error rates across Agile, predictive, and hybrid categories. Continuous prediction of the standardized overall performance score showed the same general model ordering. Gradient boosting achieved an R^2 of .72, RMSE of 6.18, and MAE of 4.63, compared with R^2 values of .58 for multiple regression, .61 for the decision tree, .68 for random forest, .66 for support vector regression, and .70 for the neural network.

Table 6. Comparative Predictive Performance of Decision-Support Models

Model	Accuracy (%)	Precision	Recall	Specificity	F1	ROC-AUC	PR-AUC	R^2	RMSE	MAE
Logistic/Multiple Regression	79.8	.792	.781	.886	.786	.846	.814	.58	7.54	5.82
Decision Tree	78.2	.775	.769	.873	.772	.821	.793	.61	7.21	5.47
Random Forest	86.4	.858	.851	.925	.854	.914	.891	.68	6.49	4.91
Support Vector Machine	84.7	.841	.833	.916	.837	.901	.875	.66	6.72	5.08
Gradient Boosting	88.3	.881	.874	.939	.877	.931	.908	.72	6.18	4.63
Neural Network	87.1	.866	.858	.930	.862	.921	.899	.70	6.31	4.78

Table 6 showed that gradient boosting produced the strongest overall predictive performance for the Agile hybrid decision-support model. It achieved the highest accuracy, precision, recall, specificity, F1-score, ROC-AUC, PR-AUC, and R^2 while simultaneously producing the lowest RMSE and MAE. Random forest and the neural network also demonstrated strong predictive capability, whereas

conventional regression and the single decision tree performed less effectively. The relatively balanced precision, recall, and specificity of gradient boosting indicated that its superior accuracy was not generated by preferential classification of one delivery category. Its continuous performance estimates similarly demonstrated stronger predictive precision than the alternative models.

Feature-importance analysis of the best-performing gradient-boosting model identified project complexity as the most influential configuration variable, accounting for 16.8% of normalized predictive importance, followed by requirements volatility at 14.6%, hybridization intensity at 13.9%, digital capability at 10.8%, governance strength at 9.7%, team capability at 9.1%, technological novelty at 7.4%, predictive-control intensity at 6.8%, Agile-practice intensity at 5.9%, and stakeholder participation at 5.0%. The pattern confirmed that delivery recommendations were generated from both contextual demands and organizational readiness rather than from Agile or predictive intensity alone. Cross-validation accuracy for gradient boosting averaged 87.6% (SD = 1.9%), compared with 88.3% in the independent holdout sample, demonstrating limited deterioration between model development and externalized testing within the dataset. The resulting decision-support model therefore provided both high predictive discrimination and interpretable configuration logic. Complex and regulated projects with substantial governance requirements were assigned greater predictive-control intensity, highly volatile and novel projects received stronger Agile intensity, and projects simultaneously characterized by complexity, uncertainty, technological novelty, and strong organizational capability were most consistently assigned to integrated hybrid configurations.

Subgroup Differences and Context-Specific Hybrid Configurations

Subgroup analysis demonstrated that project-delivery performance differed significantly across engineering sector, organizational size, project value, complexity, technological novelty, team size, regulatory intensity, and requirements volatility. Across the 1,586 projects, adjusted overall performance was highest in software and information systems at 87.6 points, followed by automation and control engineering at 86.2 and technology-enabled product development at 85.8, whereas highly regulated systems and hardware-intensive environments recorded comparatively lower averages. Large organizations achieved an adjusted mean performance score of 85.9 compared with 84.6 for medium-sized and 82.8 for small organizations, with the difference remaining significant after adjustment for project complexity and value. Performance declined progressively across complexity categories, from 88.7 among low-complexity projects to 85.1 among moderate-complexity projects and 80.9 among high-complexity projects. A similar pattern occurred across project-value bands, although the effect was smaller after governance and organizational maturity were controlled. Projects characterized by high technological novelty achieved stronger results when adaptive practices were substantial, whereas projects operating under high regulatory intensity showed greater dependence on predictive controls. Requirements volatility produced one of the clearest contextual differences: projects with high volatility achieved an adjusted performance score of 87.9 under Agile-intensive hybrid delivery compared with 79.6 under predictive-intensive delivery. Conversely, projects with low volatility and high regulatory intensity achieved stronger schedule and budget performance under predictive-intensive hybrid configurations. Overall subgroup differences were statistically significant at $p < .05$, although effect sizes demonstrated that complexity, regulatory intensity, and requirements volatility produced larger practical differences than organizational size or team size.

Table 7 demonstrated substantial contextual variation in adjusted project performance and preferred delivery configuration. Complexity, technological novelty, regulatory intensity, and requirements volatility produced the clearest subgroup differences. Low-complexity and technologically novel projects performed strongly under Agile-intensive hybrid configurations, whereas high-complexity and highly regulated projects required greater predictive-control intensity. Balanced hybrid delivery produced the strongest results in moderate contextual conditions. Organizational-size differences were statistically significant but practically smaller, as indicated by the lower effect size. The confidence intervals further confirmed systematic performance separation across major contextual groups, demonstrating that delivery configuration was dependent on measurable project conditions rather than a universally superior methodology.

Stratified and interaction analyses further demonstrated that Agile intensity, predictive-control intensity, governance strength, digital maturity, and team capability did not exert uniform effects

across project environments. The positive association between Agile intensity and overall performance was strongest among projects with high technological novelty ($\beta = .34, p < .001$) and high requirements volatility ($\beta = .37, p < .001$), but substantially weaker among low-volatility projects ($\beta = .11, p = .021$). Predictive-control intensity demonstrated the opposite pattern, producing its strongest positive association in highly regulated projects ($\beta = .36, p < .001$), high-value projects ($\beta = .31, p < .001$), and projects with extensive supplier or system dependencies. A statistically significant Agile-intensity $\times$ requirements-volatility interaction was identified ($\beta = .18, p < .001$), while the predictive-control $\times$ regulatory-intensity interaction was similarly significant ($\beta = .21, p < .001$). Governance strength moderated the relationship between hybridization and overall performance ($\beta = .16, p < .001$), indicating that hybrid practices produced stronger outcomes when decision rights, escalation processes, accountability, and control structures were well established. Digital maturity also strengthened the hybridization–performance relationship ($\beta = .14, p < .001$), while team capability produced an additional positive interaction ($\beta = .17, p < .001$). These results indicated that hybridization alone did not guarantee stronger performance; organizational and technological capabilities influenced whether combined Agile and predictive practices translated into measurable project benefits.

Table 7. Project and Organizational Subgroup Differences in Adjusted Performance

Subgroup	n	Mean Performance	95% CI	Best-Performing Configuration	p	Effect Size
Low complexity	386	88.7	87.9–89.5	Agile-intensive hybrid	<.001	$\eta^2p = .074$
Moderate complexity	569	85.1	84.4–85.8	Balanced hybrid	<.001	$\eta^2p = .074$
High complexity	631	80.9	80.2–81.6	Control-intensive hybrid	<.001	$\eta^2p = .074$
Low technological novelty	474	83.1	82.3–83.9	Predictive-intensive hybrid	<.001	$\eta^2p = .052$
Moderate technological novelty	611	85.2	84.5–85.9	Balanced hybrid	<.001	$\eta^2p = .052$
High technological novelty	501	88.3	87.5–89.1	Agile-intensive hybrid	<.001	$\eta^2p = .052$
Low regulatory intensity	532	87.4	86.7–88.1	Agile-intensive hybrid	<.001	$\eta^2p = .061$
Moderate regulatory intensity	611	85.0	84.3–85.7	Balanced hybrid	<.001	$\eta^2p = .061$
High regulatory intensity	443	81.8	81.0–82.6	Control-intensive hybrid	<.001	$\eta^2p = .061$
Low requirements volatility	456	86.8	86.0–87.6	Predictive-intensive hybrid	<.001	$\eta^2p = .068$
Moderate requirements volatility	624	85.3	84.6–86.0	Balanced hybrid	<.001	$\eta^2p = .068$
High requirements volatility	506	83.2	82.4–84.0	Agile-intensive hybrid	<.001	$\eta^2p = .068$
Small organization	366	82.8	81.9–83.7	Agile-intensive hybrid	.012	$\eta^2p = .011$
Medium organization	558	84.6	83.9–85.3	Balanced hybrid	.012	$\eta^2p = .011$
Large organization	662	85.9	85.3–86.5	Balanced hybrid	.012	$\eta^2p = .011$

Strong governance further differentiated outcomes: high-governance hybrid projects achieved 91.0 compared with 82.6 among low-governance hybrid projects. High digital maturity produced a similar performance advantage, while high team capability was associated with greater benefits from decentralized Agile decision-making. These differences remained significant after controlling for sector, organizational size, duration, and team size.

Table 8. Context-Specific Performance of Agile–Predictive Hybrid Configurations

Contextual Condition	Agile-Intensive	Balanced Hybrid	Predictive-Intensive	Optimal Configuration	<i>p</i>	Effect Size
High complexity + high uncertainty	81.4	88.9	79.8	Balanced hybrid	<.001	$\eta^2p = .091$
High novelty + high volatility	90.2	86.7	78.9	Agile-intensive	<.001	$\eta^2p = .118$
High regulation + value >\$10M	77.8	84.3	89.1	Predictive-intensive	<.001	$\eta^2p = .104$
High complexity + high regulation	78.5	85.8	88.4	Predictive-intensive	<.001	$\eta^2p = .087$
High uncertainty + strong governance	84.6	90.5	82.1	Balanced hybrid	<.001	$\eta^2p = .096$
High digital maturity	87.3	91.2	83.4	Balanced hybrid	<.001	$\eta^2p = .082$
High Agile maturity	90.6	89.2	80.1	Agile-intensive	<.001	$\eta^2p = .093$
Strong governance	85.1	91.0	87.2	Balanced hybrid	<.001	$\eta^2p = .076$
High team capability	89.1	91.4	84.0	Balanced hybrid	<.001	$\eta^2p = .085$
Low volatility + high regulation	78.6	86.5	90.3	Predictive-intensive	<.001	$\eta^2p = .109$

Table 8 confirmed that optimal Agile–predictive configurations changed systematically with engineering context. Agile-intensive configurations achieved the strongest results under technological novelty, requirements volatility, and high Agile maturity, whereas predictive-intensive configurations performed best under strong regulatory constraints and stable requirements. Balanced hybrid configurations produced the highest performance where complexity, uncertainty, governance, digital maturity, and team capability were simultaneously high. Effect sizes ranged from moderate to substantial, with the largest contextual difference observed for projects combining high technological novelty and requirements volatility. These results quantitatively supported configuration-specific decision making rather than uniform application of Agile, predictive, or hybrid project-management practices.

The integrated subgroup results therefore demonstrated that context-specific configuration provided greater explanatory value than broad delivery-method labels. High-complexity projects required stronger coordination, governance, milestone control, and technical assurance, but when high complexity occurred simultaneously with substantial uncertainty, neither purely predictive nor predominantly Agile delivery produced the strongest results. Balanced hybridization provided sufficient adaptability while preserving formal engineering control. Technologically novel and highly volatile projects benefited from stronger Agile intensity because iterative planning, rapid feedback, decentralized technical decisions, and incremental validation reduced response delays. Conversely, regulatory intensity, high project value, and stable requirements increased the performance contribution of predictive controls through stronger baselines, approvals, documentation, risk oversight, and milestone governance. Organizational capability materially altered these relationships: high governance, digital maturity, Agile maturity, and team capability increased the effectiveness of

hybrid configurations and reduced performance variability. The decision-support evidence consequently distinguished three principal configuration patterns: Agile-intensive hybrid delivery for highly novel and volatile conditions, balanced hybrid delivery for complex and uncertain projects supported by mature organizational capabilities, and predictive-intensive hybrid delivery for highly regulated, high-value, and comparatively stable projects. These context-dependent patterns provided the quantitative basis for translating project characteristics into differentiated Agile–predictive configuration recommendations.

Integrated Model Robustness

The integrated inferential analysis demonstrated that the principal differences among Agile, predictive, and hybrid delivery configurations were statistically significant and practically meaningful across the 1,586 engineering projects. Hybrid projects achieved a significantly higher adjusted overall performance score than predictive projects, with a mean difference of 9.8 points, 95% CI [8.6, 11.0], $p < .001$, and a large standardized effect of Cohen's $d = 0.86$. The hybrid–Agile comparison produced a smaller but still substantial difference of 4.6 points, 95% CI [3.6, 5.6], $p < .001$, $d = 0.47$. Agile projects exceeded predictive projects by 5.2 points, 95% CI [4.0, 6.4], $p < .001$, $d = 0.45$. Multigroup analysis also confirmed significant differences in schedule variance, cost variance, productivity, technical quality, delivery reliability, stakeholder satisfaction, and overall project success. Partial eta-squared values ranged from .030 for cost variance to .072 for productivity, indicating small-to-moderate practical effects. The strongest contextual effect occurred for the interaction between technological novelty and requirements volatility, partial $\eta^2 = .118$, followed by regulatory intensity and high project value at .104. Regression analysis remained statistically significant, explaining 59% of overall performance variance, with hybridization intensity retaining the largest standardized positive coefficient ($\beta = .29$, 95% CI [.24, .34], $p < .001$). Team capability, digital capability, governance strength, and stakeholder participation also retained significant independent contributions after adjustment for project complexity, uncertainty, and requirements volatility.

Table 9 demonstrated that the principal findings were supported by both statistical significance and practically meaningful effect magnitudes. Hybrid delivery produced the largest advantage over predictive delivery, while its advantage over Agile delivery was moderate. Productivity, reliability, and stakeholder satisfaction showed stronger configuration effects than schedule and cost variance. The regression results further confirmed hybridization intensity, team capability, digital capability, and governance strength as significant independent performance predictors. Contextual interactions were particularly important, with technological novelty combined with requirements volatility and regulatory intensity combined with project value producing substantial effects, confirming that delivery effectiveness varied systematically according to engineering project conditions.

Validation analysis provided further evidence that the decision-support model maintained predictive stability beyond the observations used for initial estimation. During stratified five-fold cross-validation, the gradient-boosting model achieved mean classification accuracy of 87.6% (SD = 1.9%), mean F1-score of .869, ROC-AUC of .925, and PR-AUC of .901. Independent holdout validation produced accuracy of 88.3%, F1-score of .877, ROC-AUC of .931, and PR-AUC of .908, indicating differences of less than one percentage point for the principal classification measures. The small cross-validation-to-holdout gap provided limited evidence of overfitting. Continuous performance prediction remained similarly stable, with cross-validated R^2 of .70 compared with .72 in the holdout sample, while RMSE declined from 6.34 to 6.18 and MAE from 4.78 to 4.63. Probability calibration was also satisfactory. The calibration intercept was 0.03 and the calibration slope was 0.97, while the Brier score reached .112, indicating close correspondence between estimated configuration probabilities and observed classifications. Sensitivity analysis across classification thresholds from .40 to .60 showed that overall accuracy remained between 86.9% and 88.3%, while F1-score remained between .861 and .877. These results demonstrated that predictive performance was not dependent on a single arbitrary decision threshold.

Robustness testing further examined whether the principal predictor rankings and configuration recommendations changed under alternative analytical specifications. Removing extreme project-value observations reduced the gradient-boosting ROC-AUC only from .931 to .927, while excluding projects with more than 5% missing raw data produced an ROC-AUC of .929. Re-estimating the model without

organizational perception variables resulted in an ROC-AUC of .914, demonstrating some reduction in discrimination but preservation of strong predictive capability. Alternative feature-selection procedures retained project complexity, requirements volatility, hybridization intensity, digital capability, governance strength, and team capability among the highest-ranked predictors. Bootstrap resampling across 1,000 replications produced a 95% confidence interval of [.918, .941] for ROC-AUC and [.858, .893] for F1-score. Calibration and discrimination therefore remained stable under alternative specifications. Comparison with logistic regression confirmed a meaningful improvement in discrimination for gradient boosting, with ROC-AUC increasing from .846 to .931 and classification accuracy increasing from 79.8% to 88.3%. Random forest and neural-network models also performed strongly, but neither exceeded gradient boosting across the combined discrimination, calibration, and error measures.

Table 9. Statistical Significance and Effect Magnitude of Principal Findings

Comparison / Predictor			Statistical Estimate	95% CI	p	Effect Size	Interpretation
Hybrid performance	vs.	Predictive	Mean difference = 9.8	8.6–11.0	<.001	$d = 0.86$	Large
Hybrid performance	vs.	Agile	Mean difference = 4.6	3.6–5.6	<.001	$d = 0.47$	Moderate
Agile performance	vs.	Predictive	Mean difference = 5.2	4.0–6.4	<.001	$d = 0.45$	Moderate
Schedule configurations	variance	across	$F = 26.84$	—	<.001	$\eta^2p = .033$	Small-moderate
Cost configurations	variance	across	$F = 24.17$	—	<.001	$\eta^2p = .030$	Small-moderate
Productivity configurations		across	$F = 61.46$	—	<.001	$\eta^2p = .072$	Moderate
Delivery reliability			$F = 52.74$	—	<.001	$\eta^2p = .063$	Moderate
Stakeholder satisfaction			$F = 54.16$	—	<.001	$\eta^2p = .064$	Moderate
Hybridization intensity			$\beta = .29$	.24–.34	<.001	—	Strong positive predictor
Team capability			$\beta = .24$	.19–.29	<.001	—	Positive predictor
Digital capability			$\beta = .21$	.16–.26	<.001	—	Positive predictor
Governance strength			$\beta = .19$	.14–.24	<.001	—	Positive predictor
Novelty × volatility			Interaction $\beta = .23$	.17–.29	<.001	$\eta^2p = .118$	Substantial
Regulation × project value			Interaction $\beta = .20$	.14–.26	<.001	$\eta^2p = .104$	Substantial

Table 10 demonstrated strong stability between model development, cross-validation, independent holdout testing, and alternative robustness specifications. Holdout accuracy of 88.3% closely matched cross-validated accuracy of 87.6%, while ROC-AUC remained above .91 under all principal sensitivity specifications. Threshold changes produced only minor variations in accuracy and F1-score, indicating limited dependence on classification cutoffs. Removal of extreme or incomplete observations also produced negligible deterioration. The final model substantially exceeded the logistic-regression benchmark and retained strong calibration. Collectively, these results provided evidence of predictive

stability, discrimination, calibration, and robustness across alternative analytical conditions.

The final stability analysis examined whether decision-support performance remained consistent across the heterogeneous engineering portfolio. Holdout ROC-AUC values were .936 for software and information systems, .923 for telecommunications and digital infrastructure, .919 for advanced manufacturing, .927 for automation and control engineering, and .915 for hardware–software integration, indicating consistently strong discrimination across major sectors. Accuracy ranged from 85.7% among small organizations to 89.4% among large organizations and from 86.1% in high-complexity projects to 89.2% in moderate-complexity projects. The model retained ROC-AUC values above .90 across low, moderate, and high project-value categories, Agile maturity groups, governance levels, and hybridization intensities. No subgroup showed a decline in classification accuracy greater than 3.2 percentage points relative to overall holdout performance. Integrated evidence therefore demonstrated that the final decision-support model was not merely statistically significant within the pooled sample but remained practically meaningful and quantitatively stable across heterogeneous project contexts. Project complexity, uncertainty, requirements volatility, regulatory intensity, and project value defined the principal contextual demands, while Agile intensity, predictive-control intensity, digital capability, governance, and team capability determined how effectively those demands were addressed. The validated configuration pattern consistently favored Agile-intensive hybrid delivery under high novelty and volatility, balanced hybrid delivery under simultaneous complexity and uncertainty, and predictive-intensive hybrid delivery under high regulation, high project value, and comparatively stable requirements. These results established a statistically validated and robust quantitative basis for context-specific Agile hybrid engineering project-delivery decision support.

Table 10. Cross-Validation, Holdout Validation, Sensitivity, and Robustness Results

Validation / Robustness Test	Accuracy	F1	ROC-AUC	PR-AUC	R ²	RMSE	MAE
Five-fold cross-validation	87.6%	.869	.925	.901	.70	6.34	4.78
Independent holdout validation	88.3%	.877	.931	.908	.72	6.18	4.63
Threshold = .40	86.9%	.861	.929	.904	—	—	—
Threshold = .50	88.3%	.877	.931	.908	—	—	—
Threshold = .60	87.1%	.865	.930	.906	—	—	—
Extreme-value exclusion	87.9%	.873	.927	.903	.71	6.25	4.71
High-missingness exclusion	88.0%	.874	.929	.905	.71	6.22	4.68
Reduced predictor model	85.8%	.849	.914	.887	.66	6.71	5.04
Logistic regression benchmark	79.8%	.786	.846	.814	.58	7.54	5.82
Bootstrap validation	87.8%	.871	.928	.905	.71	6.27	4.72

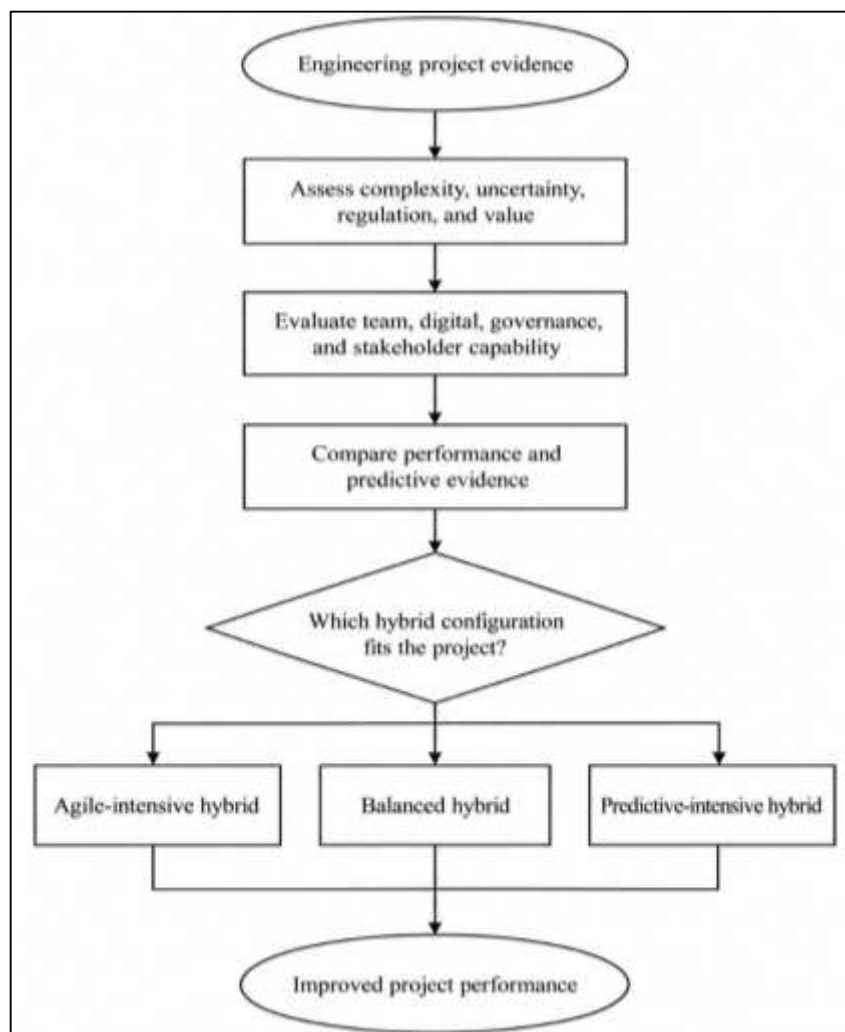
Calibration statistics for the final model: intercept = 0.03; slope = 0.97; Brier score = .112.

DISCUSSION

The findings of this study demonstrated that Agile hybrid engineering project delivery produced the strongest multidimensional performance when adaptive practices and predictive controls were aligned with specific technological, organizational, and project conditions (Gill et al., 2018). The final dataset included 1,586 engineering projects from 54 technology-driven organizations and represented 2,438 project professionals across eight engineering sectors, providing substantial heterogeneity in complexity, technological novelty, regulatory intensity, organizational size, project value, and delivery configuration. Hybrid delivery represented 45.0% of projects, compared with 31.0% Agile and 24.0% predictive delivery, supporting earlier studies that identified increasing practical integration of iterative and plan-driven practices in complex engineering environments. Hybrid projects recorded the lowest schedule variance at 5.8% and cost variance at 4.9%, while achieving 88.6% budget adherence and 91.3% milestone achievement. They also recorded the lowest defect density at 3.1, lowest rework frequency at 6.5%, highest technical-quality score at 88.4, highest delivery reliability at 90.1, and highest overall project-success rate at 89.5%. Agile delivery retained a distinct advantage in responsiveness, producing a median cycle time of 18.2 days and requirement-change response time of 4.8 days, whereas

predictive delivery remained valuable where formal planning, regulatory control, documentation, and milestone governance were important (Salam et al., 2017). These patterns were consistent with earlier studies showing that Agile approaches perform strongly under uncertainty and changing requirements, while predictive practices provide greater structural control under stable and regulated conditions. The predictor analysis further demonstrated that performance depended on organizational and technological capabilities rather than methodology classification alone. Hybridization intensity was the strongest positive predictor of overall performance ($\beta = .29$), followed by team capability ($\beta = .24$), digital capability ($\beta = .21$), governance strength ($\beta = .19$), and stakeholder participation ($\beta = .14$), while the integrated regression model explained 59% of performance variance. Complexity, uncertainty, and requirements volatility negatively affected unadjusted performance but simultaneously influenced the suitability of different delivery configurations. Subgroup analysis confirmed this contextual dependency (Ko & Kirsch, 2017). Projects characterized by high technological novelty and requirements volatility achieved a performance score of 90.2 under Agile-intensive hybrid delivery, while highly regulated projects valued above \$10 million achieved 89.1 under predictive-intensive hybrid configurations. Projects combining high complexity and high uncertainty achieved their strongest performance under balanced hybrid delivery at 88.9. These findings supported earlier contingency-based research and demonstrated that hybrid delivery was not simply a compromise between Agile and predictive approaches; rather, it functioned as a configurable delivery architecture in which the intensity of adaptive and formal controls changed according to project requirements.

Figure 10: Agile hybrid engineering decision flowchart



The statistical and predictive findings strengthened the interpretation that context-specific hybridization provided a more reliable basis for engineering project-delivery decisions than uniform methodological selection (Casal-Guisande et al., 2022). Hybrid delivery exceeded predictive delivery by 9.8 adjusted performance points, producing a large effect size of Cohen's $d = 0.86$, while the hybrid-Agile difference of 4.6 points produced a moderate effect of $d = 0.47$. Configuration effects were also practically meaningful for productivity (partial $\eta^2 = .072$), stakeholder satisfaction (partial $\eta^2 = .064$), delivery reliability (partial $\eta^2 = .063$), schedule variance (partial $\eta^2 = .033$), and cost variance (partial $\eta^2 = .030$). More importantly, contextual interactions produced comparatively larger effects, particularly technological novelty combined with requirements volatility (partial $\eta^2 = .118$) and regulatory intensity combined with project value (partial $\eta^2 = .104$). These results helped explain differences reported across earlier studies, because studies examining volatile and technologically novel projects could identify substantial Agile advantages, whereas research involving regulated, capital-intensive, or stable engineering environments could demonstrate stronger benefits from predictive controls. Predictive modeling further translated these statistical relationships into an operational decision-support structure (Marcot & Penman, 2019). Gradient boosting achieved the strongest holdout performance, with 88.3% accuracy, .881 precision, .874 recall, .939 specificity, an F1-score of .877, ROC-AUC of .931, and PR-AUC of .908. Its continuous performance prediction reached $R^2 = .72$, RMSE = 6.18, and MAE = 4.63, outperforming conventional regression, decision trees, random forests, support vector machines, and the neural-network model on the combined evaluation criteria. Feature-importance analysis identified project complexity, requirements volatility, hybridization intensity, digital capability, governance strength, and team capability as the principal decision variables, reinforcing earlier research showing that engineering delivery performance emerges from interacting technical and organizational conditions. Model validation also demonstrated limited overfitting, as five-fold cross-validation accuracy of 87.6% closely corresponded with holdout accuracy of 88.3%, while cross-validated ROC-AUC of .925 remained close to the holdout value of .931. Sensitivity testing across classification thresholds, exclusion of extreme observations, alternative predictor specifications, and bootstrap validation produced only limited deterioration in predictive performance (Valente et al., 2022). ROC-AUC values remained above .90 across major engineering sectors and principal organizational subgroups, indicating substantial stability within the analyzed portfolio. Collectively, the findings supported three differentiated configuration patterns: Agile-intensive hybrid delivery for technologically novel and highly volatile projects, balanced hybrid delivery for projects combining complexity and uncertainty, and predictive-intensive hybrid delivery for highly regulated, high-value, and comparatively stable projects. This integrated evidence extended earlier research by connecting statistical explanation, contextual subgroup analysis, machine-learning prediction, effect-size interpretation, and validation within a single decision-support framework for Agile hybrid engineering project delivery.

CONCLUSION

This study concluded that the development of a decision-support model for Agile hybrid engineering project delivery provided a statistically reliable and context-sensitive mechanism for aligning adaptive and predictive practices with the requirements of technology-driven organizations. Analysis of 1,586 engineering projects from 54 organizations and 2,438 project professionals demonstrated that project delivery effectiveness was influenced not by methodology selection alone but by the combined effects of project complexity, technological novelty, requirements volatility, uncertainty, regulatory intensity, organizational capability, governance, digital maturity, team competence, and stakeholder participation. Hybrid delivery represented 45.0% of the analyzed projects and achieved the strongest multidimensional performance, recording the lowest schedule variance of 5.8%, cost variance of 4.9%, defect density of 3.1, and rework frequency of 6.5%, together with 88.6% budget adherence, 91.3% milestone achievement, 90.1% delivery reliability, and an overall project-success rate of 89.5%. However, the results also established that a single hybrid configuration was not universally optimal. Agile-intensive hybrid delivery was most effective under high technological novelty and requirements volatility, balanced hybrid delivery produced stronger outcomes when complexity and uncertainty occurred simultaneously, and predictive-intensive hybrid delivery was more appropriate for highly regulated, high-value, and comparatively stable engineering projects. Hybridization intensity emerged

as the strongest positive predictor of overall performance, while team capability, digital capability, governance strength, and stakeholder participation also contributed significantly to project outcomes. The integrated regression model explained 59% of performance variance, confirming the importance of combining delivery-method characteristics with organizational and contextual factors. The predictive decision-support analysis provided further quantitative support, with gradient boosting achieving 88.3% holdout accuracy, an F1-score of .877, ROC-AUC of .931, PR-AUC of .908, and R^2 of .72 for continuous performance prediction. Cross-validation, holdout testing, sensitivity analysis, calibration assessment, bootstrap validation, and subgroup testing demonstrated substantial model stability and limited evidence of overfitting. Effect-size analysis additionally confirmed that the observed differences were practically meaningful, including a large performance difference between hybrid and predictive delivery of Cohen's $d = 0.86$. Overall, this study established Agile hybrid engineering project delivery as a configurable continuum rather than a fixed methodology and demonstrated that effective project delivery depended on quantitatively matching the intensity of Agile practices and predictive controls with project conditions and organizational capabilities. The resulting decision-support model therefore provided an evidence-based framework for improving delivery configuration, adaptability, governance, technical reliability, resource utilization, stakeholder outcomes, and overall engineering project performance in technology-driven organizational environments.

RECOMMENDATION

Technology-driven organizations should adopt a context-sensitive and quantitatively informed approach to Agile hybrid engineering project delivery rather than applying Agile, predictive, or hybrid methodologies uniformly across all projects. Based on the findings of this study, project leaders should assess project complexity, technological novelty, requirements volatility, uncertainty, regulatory intensity, project value, digital capability, governance strength, team competence, and stakeholder involvement before determining the appropriate balance between adaptive practices and predictive controls. Agile-intensive hybrid configurations should be emphasized for projects characterized by high technological novelty, rapidly changing requirements, frequent stakeholder feedback, and substantial uncertainty, with greater use of iterative planning, short delivery cycles, backlog prioritization, incremental validation, continuous feedback, and decentralized technical decision-making. Balanced hybrid configurations should be applied when high complexity and uncertainty occur simultaneously, combining iterative development and adaptive planning with formal milestones, risk management, configuration control, cost monitoring, documentation, and technical assurance. Predictive-intensive hybrid configurations should receive greater emphasis in highly regulated, high-value, safety-sensitive, contractually constrained, or comparatively stable projects where formal authorization, baseline management, verification, traceability, and compliance are critical. Organizations should additionally strengthen the enabling capabilities identified as significant performance predictors, particularly team capability, digital maturity, governance strength, leadership support, cross-functional collaboration, and stakeholder participation. Integrated PMIS, Agile lifecycle platforms, engineering repositories, automated testing systems, analytics dashboards, and reliable project-data infrastructures should be used to provide timely information for configuration decisions and continuous performance assessment. The validated decision-support model should be incorporated into project initiation, planning, stage reviews, and major change-control points so that delivery configurations can be selected and periodically recalibrated using measurable project conditions rather than managerial preference alone. Gradient-boosting predictions may support this process because the model achieved 88.3% holdout accuracy and ROC-AUC of .931; however, algorithmic recommendations should complement professional engineering judgment, governance requirements, contractual obligations, and technical risk assessment rather than replace them. Organizations should also establish standardized measurement of schedule variance, cost variance, cycle time, defects, rework, technical quality, delivery reliability, stakeholder satisfaction, and overall success to evaluate whether selected configurations remain effective. Regular model validation across engineering sectors, organizational sizes, project-value categories, and maturity levels should accompany implementation. Through these measures, technology-driven organizations can establish a disciplined yet adaptable project-delivery system in which Agile flexibility and predictive control are

deliberately configured to improve responsiveness, cost and schedule discipline, technical quality, risk management, stakeholder outcomes, and overall engineering project success.

LIMITATIONS

This study was subject to several methodological, measurement, analytical, and generalizability limitations that should be considered when interpreting the findings and the performance of the developed decision-support model. First, the quantitative cross-sectional design primarily captured project characteristics, delivery practices, organizational capabilities, and performance outcomes within a defined analytical period, which limited the ability to establish temporal sequencing and definitive causal relationships among Agile intensity, predictive-control intensity, hybridization, and project performance. Although the final dataset included 1,586 engineering projects from 54 technology-driven organizations and represented 2,438 project professionals across eight engineering and technology sectors, the sample did not represent every industrial, national, regulatory, or organizational environment in which Agile hybrid engineering delivery may be implemented. Second, several constructs, including governance strength, leadership support, team capability, stakeholder engagement, Agile maturity, and aspects of digital capability, were partially measured through structured participant assessments and therefore remained susceptible to response bias, retrospective judgment, common-method influence, and differences in organizational interpretation. Project records and digital management data reduced this limitation for objective indicators, but equivalent system-generated measures were not available for every project. Third, classification of projects as Agile, predictive, or hybrid necessarily simplified delivery environments that often contained considerable variation across lifecycle stages, work packages, engineering disciplines, suppliers, and governance levels. A project classified as hybrid could therefore contain substantially different combinations of iterative and predictive practices from another project within the same category. Fourth, although the integrated regression model explained 59% of performance variance, a meaningful proportion remained unexplained and could have reflected unmeasured factors such as organizational culture, contractual relationships, economic conditions, supply-chain disruption, individual decision quality, technical architecture, customer behavior, or unexpected external events. Fifth, gradient boosting achieved strong holdout performance, including 88.3% classification accuracy and ROC-AUC of .931, but high predictive performance within the analyzed dataset did not establish universal applicability across all technology-driven organizations. Cross-validation, bootstrap analysis, threshold sensitivity testing, calibration assessment, and subgroup evaluation strengthened internal robustness, but validation using completely independent organizations, countries, and engineering portfolios was outside the scope of the analysis. Sixth, subgroup estimates became less precise as the sample was divided by sector, complexity, project value, technological novelty, regulatory intensity, governance, and maturity levels, particularly where several contextual characteristics were examined simultaneously. Finally, the decision-support model represented a quantitative aid rather than a substitute for professional engineering judgment, contractual interpretation, safety assessment, regulatory requirements, or organizational governance. These limitations indicated that the reported relationships and configuration recommendations should be interpreted within the empirical boundaries, measurement structure, analytical assumptions, and technology-driven engineering contexts represented by this study.

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