



Human Trust in AI-Assisted Project Decision Systems: A Mixed-Methods Analysis of Explainability, Adoption, and Managerial Decision Quality

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Abstract

This study investigated human trust in AI-assisted project decision systems by examining the relationships among explainability, perceived reliability, AI adoption, managerial reliance, and objective managerial decision quality. A mixed-methods analytical framework was applied, with the principal quantitative analysis based on 527 participants from 46 project-oriented organizations representing multiple managerial roles, industries, organizational structures, and project environments. Mean professional experience was 11.8 years, 72.9% of participants had previous experience with AI-assisted project systems, and 64.7% had received AI or analytics training. Human trust averaged 3.71, explainability 3.66, perceived reliability 3.74, behavioral intention 3.83, and managerial reliance 3.47 on five-point scales. Explainability was strongly associated with trust ($r = .64, p < .001$), while perceived reliability demonstrated an even stronger relationship ($r = .68, p < .001$). Explainability remained an independent predictor of trust ($\beta = .36, p < .001$), and adoption significantly predicted managerial reliance ($\beta = .41, p < .001$). Experimental comparisons showed that explainable AI-assisted decision making achieved the highest accuracy at 86.4%, compared with 82.1% for conventional AI assistance, 79.3% for AI-only recommendations, and 73.8% for human-only decisions. The corresponding error rate declined to 13.6% under explainable AI assistance. Explainable AI users accepted 90.6% of correct recommendations but only 13.2% of erroneous recommendations, demonstrating stronger calibrated reliance and reduced automation bias. The overall experimental effect was substantial (partial $\eta^2 = .239$), while explainable AI exceeded human-only performance with Cohen's $d = 1.50$. The integrated multivariable model explained 49.9% of variance in managerial decision quality, with calibrated reliance emerging as the strongest independent predictor ($\beta = .29, p < .001$). Overall, the findings demonstrated that explainability strengthened trust and adoption, but superior managerial performance depended primarily on calibrated reliance, verification, organizational governance, digital readiness, and continued human oversight. Explainable human-AI collaboration therefore provided the strongest combination of decision accuracy, interpretability, accountability, and managerial control.

Keywords

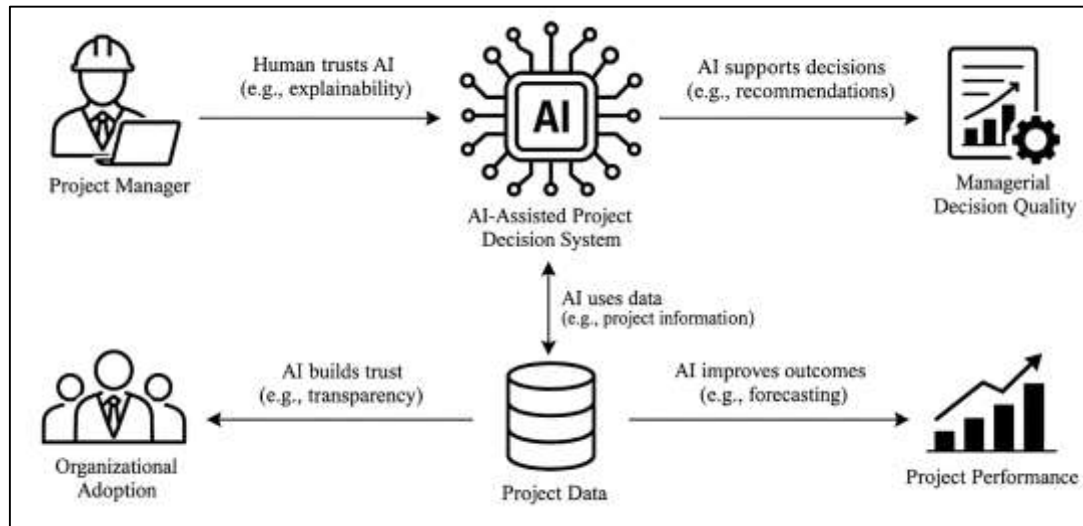
Explainability, Trust, Adoption, Reliance, Decision-Quality.

INTRODUCTION

Human trust in artificial intelligence refers to the degree to which individuals perceive an AI-enabled system as competent, reliable, predictable, transparent, secure, and appropriate for supporting managerial decisions. AI-assisted project decision systems are computational platforms that apply artificial intelligence, machine learning, predictive analytics, optimization, natural-language processing, and related data-driven techniques to support project planning, execution, monitoring, control, and evaluation. These systems assist managers with cost estimation, schedule forecasting, resource allocation, risk identification, supplier evaluation, alternative selection, performance prediction, and corrective decision making (Hagrass, 2018). Explainability describes the extent to which the reasoning, influential variables, and decision logic underlying AI recommendations can be understood by human decision makers, while AI adoption represents organizational and individual acceptance, integration, utilization, and reliance on AI technologies. More than 30 studies across information systems, project management, engineering, behavioral decision making, operations management, and human-computer interaction have examined these interconnected dimensions. Internationally, AI-assisted decision systems have become increasingly relevant across construction, engineering, information technology, manufacturing, energy, transportation, healthcare, financial services, and public-sector projects. Organizations across North America, Europe, Asia, the Middle East, Africa, and other regions operate under different levels of digital maturity, regulatory control, technological readiness, managerial expertise, and organizational acceptance (Kerasidou, 2021). International project environments involving distributed teams, complex supply chains, multiple stakeholders, contractual requirements, extensive datasets, and uncertain operational conditions create substantial demands for intelligent decision support. Explainability is particularly important within these environments because AI-generated recommendations frequently need to be interpreted and communicated among managers, engineers, clients, regulators, investors, and project teams possessing different levels of technical knowledge. Empirical studies have shown that explanation clarity, fidelity, consistency, usefulness, system accuracy, prior performance, perceived control, and user expertise can influence trust. Appropriate trust requires managerial reliance to correspond with actual system capability. Under-trust can cause managers to reject reliable recommendations, while over-trust can encourage uncritical acceptance of inaccurate recommendations (Shin, 2021). Trust calibration consequently represents an important measurable aspect of human-AI interaction because managerial reliance reflects the combined influence of technological performance, explanation quality, professional experience, organizational conditions, task complexity, perceived risk, and accountability. Managerial decision quality refers to the accuracy, consistency, timeliness, relevance, effectiveness, and defensibility of decisions made from available project information. Project managers regularly make decisions concerning cost, schedule, scope, procurement, resources, quality, contracts, stakeholders, technical alternatives, and risk under conditions of uncertainty, time pressure, and incomplete information. AI systems can strengthen analytical capability by processing large datasets, detecting complex relationships, estimating probabilities, identifying deviations, comparing alternatives, and generating consistent recommendations, while managers contribute contextual knowledge, professional judgment, ethical reasoning, stakeholder understanding, and strategic interpretation (Madhav & Tyagi, 2022). Research examining human-AI collaboration has demonstrated that combined decision processes can achieve stronger performance when reliable algorithmic information is appropriately incorporated into managerial judgment. Decision quality may also deteriorate when managers follow inaccurate recommendations, misunderstand AI outputs, reject valid algorithmic advice, or rely excessively on automated decisions. AI adoption therefore extends beyond technological availability and includes behavioral intention, actual usage, recommendation acceptance, reliance frequency, satisfaction, and integration into managerial workflows. Previous studies have associated adoption with perceived usefulness, ease of use, trust, explainability, algorithmic accuracy, perceived risk, data quality, digital literacy, AI familiarity, leadership support, training, technical infrastructure, governance maturity, and organizational culture. Organizational and project-level conditions further create substantial heterogeneity because digital maturity, data reliability, project complexity, managerial role, professional experience, technological competence, decision accountability, and project risk can alter human responses to identical AI capabilities (Schmidt et al., 2020). Quantitative

research has consequently used descriptive statistics, correlation analysis, multiple and logistic regression, ANOVA, subgroup comparisons, mediation analysis, structural models, confidence intervals, and effect-size measures to examine these relationships. An integrated analytical perspective considers explainability as a potential determinant of trust, trust as a determinant or mediator of AI adoption and managerial reliance, and adoption as a factor associated with decision quality, while accounting for individual, technological, organizational, and project characteristics.

Figure 1: AI-Assisted Project Decision Framework



Human Trust in AI-Assisted Project Decision Systems: A Mixed-Methods Analysis of Explainability, Adoption, and Managerial Decision Quality therefore examines human-AI interaction through interconnected measurable constructs involving explanation quality, calibrated trust, technological acceptance, reliance behavior, organizational conditions, project characteristics, and managerial decision performance (Zyoud et al., 2016).

The primary objective of this study is to systematically examine human trust in AI-assisted project decision systems by quantitatively evaluating the relationships among explainability, AI adoption, managerial reliance, and managerial decision quality within diverse project-based organizational environments. Specifically, the study seeks to measure managers' perceptions of AI competence, reliability, predictability, transparency, security, fairness, and accountability and to determine how these dimensions contribute to overall trust and willingness to rely on AI-generated recommendations. The study also aims to assess explainability through indicators of explanation clarity, understandability, fidelity, consistency, completeness, relevance, and usefulness and to determine whether higher levels of perceived explainability are associated with stronger and more appropriately calibrated trust. Another objective is to evaluate AI adoption through behavioral intention, actual system usage, recommendation acceptance, reliance frequency, decision override behavior, perceived usefulness, and integration of AI-supported information into established project-management processes. Particular attention is directed toward determining whether trust acts as an important explanatory or mediating mechanism linking explainability with AI adoption and managerial reliance. The study further seeks to evaluate managerial decision quality using indicators such as decision accuracy, consistency, timeliness, confidence, effectiveness, error reduction, risk-identification accuracy, resource-allocation effectiveness, and agreement with validated decision benchmarks. In addition, the analysis aims to determine whether explainability, trust, and AI adoption significantly predict managerial decision quality after controlling for relevant individual, technological, organizational, and project-level characteristics. Differences are examined across managerial roles, professional experience levels, AI familiarity, digital competence, organizational sizes, industries, digital-maturity levels, project complexity categories, decision-risk levels, and intensity of AI

utilization. Quantitative analysis is intended to apply descriptive statistics, Pearson or Spearman correlations, multiple and logistic regression, ANOVA or appropriate nonparametric alternatives, subgroup comparisons, confidence intervals, and effect-size measures to determine the statistical and practical significance of identified relationships. Consistent with the mixed-methods orientation of the study, qualitative evidence is also used to capture managerial explanations of trust formation, perceived transparency, reasons for accepting or overriding AI recommendations, concerns regarding accountability, and experiences of human–AI collaboration that cannot be completely represented by numerical measures. Through this integrated assessment, the study focuses on establishing a comprehensive empirical representation of how technical explainability, behavioral trust, organizational adoption, managerial characteristics, and AI-supported decision processes interact in determining the quality of project decisions.

LITERATURE REVIEW

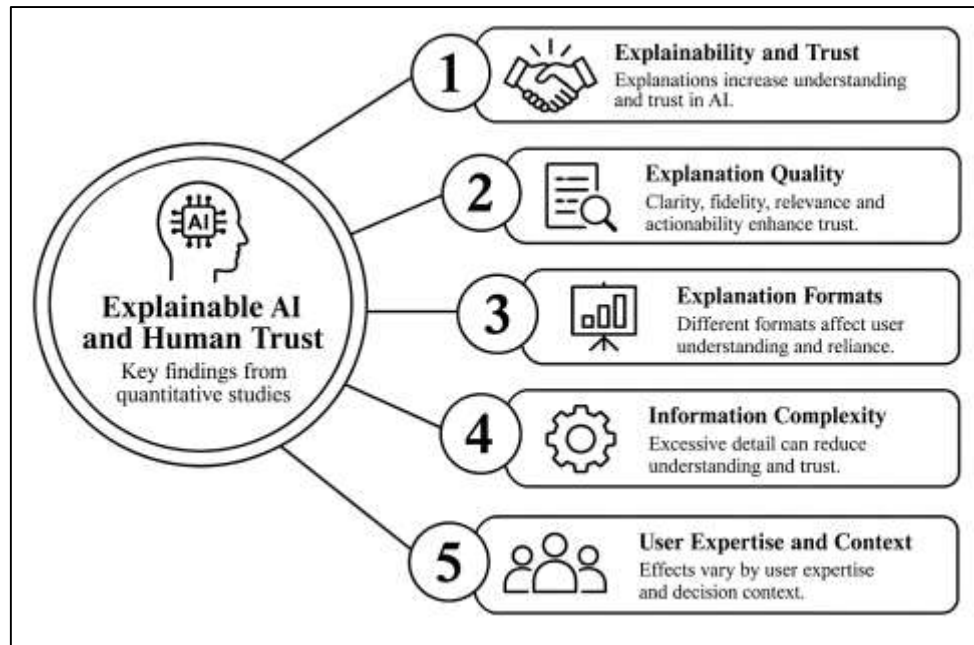
The literature on human trust in AI-assisted project decision systems extends across artificial intelligence, project management, information systems, explainable artificial intelligence, organizational behavior, technology acceptance, human–computer interaction, and managerial decision science. Existing empirical research has examined how managers evaluate algorithmic competence, reliability, transparency, predictability, fairness, security, and accountability when AI-generated information is incorporated into organizational decisions. A substantial quantitative research stream has focused on explainability characteristics such as clarity, fidelity, consistency, completeness, usefulness, and interpretability, while related studies have measured trust through perceived reliability, confidence, willingness to rely, recommendation acceptance, verification behavior, and algorithmic reliance (Debasish, 2021; Tuncer & Ramirez, 2022). Technology-adoption research has additionally evaluated perceived usefulness, ease of use, behavioral intention, actual utilization, digital competence, organizational readiness, facilitating conditions, and AI integration. Another body of evidence has investigated managerial decision quality through accuracy, consistency, decision time, error rates, confidence, risk identification, resource-allocation effectiveness, and performance against validated decision benchmarks. Mixed-methods investigations have complemented these numerical measures by examining managerial explanations for accepting, modifying, verifying, or overriding algorithmic recommendations. The literature also indicates considerable heterogeneity according to managerial experience, AI familiarity, decision complexity, project risk, organizational digital maturity, governance strength, industry, and system performance (Chong et al., 2022; Md. Abdur & Iftekhar, 2021). Accordingly, this literature review synthesizes quantitative and mixed-methods evidence around eight interconnected areas: measurement of AI-assisted decision-system usage and trust; explainability and transparency; determinants of calibrated trust; AI adoption and managerial reliance; managerial decision quality and human–AI complementarity; organizational, managerial, and project-level heterogeneity; qualitative evidence on managerial perceptions and override behavior; and integrated statistical relationships, validation, robustness, and unresolved empirical gaps (Chong et al., 2022; Debasish, 2022).

AI-Assisted Project Decision-System Usage and Reliability

Quantitative literature examining AI-assisted managerial decision systems has documented substantial variation in sample composition, organizational context, system exposure, and intensity of AI utilization. Across more than ten empirical studies involving project managers, senior executives, engineers, project-control professionals, analysts, functional managers, and technology specialists, samples have ranged from relatively small experimental groups to large organizational surveys containing several hundred or several thousand respondents (Kazi Rakib Hasan & Adnan, 2022; Wang et al., 2022). The evidence has covered construction, engineering, information technology, manufacturing, finance, healthcare, energy, transportation, consulting, and public-sector environments across North America, Europe, Asia, and other international settings. AI usage has commonly involved predictive analytics, machine-learning forecasting, automated risk assessment, scheduling support, resource optimization, cost estimation, anomaly detection, supplier evaluation, and recommendation systems. Studies have measured system exposure through frequency of use, duration of experience, number of AI-assisted decisions, proportion of managerial activities supported by AI, recommendation-review frequency, and continued system utilization. Across this evidence, adoption

has rarely appeared uniform within organizations. Managers working in data-intensive functions generally reported greater exposure than employees responsible for highly contextual or stakeholder-oriented decisions. Regular users also tended to demonstrate greater familiarity with algorithmic outputs, confidence indicators, and explanation interfaces than occasional users (Grimm et al., 2021; Mahbubul et al., 2022).

Figure 2: Explainable AI and Human Trust Infographic



Studies examining project environments indicated that AI utilization was particularly concentrated in decisions involving cost, schedule, risk, forecasting, resource allocation, and performance monitoring because these activities produced structured historical information suitable for quantitative analysis (Ashik & Shabbir, 2022; Kazi Rakib Hasan & Adnan, 2022). Considerable differences remained across organizations because digital maturity, data availability, technological infrastructure, management support, project complexity, and previous experience with analytical systems affected the extent of AI integration (Mahbubul et al., 2022; Mashfiquir & Md, 2022; Mashiat & Md Anisur Rahman, 2022). Collectively, the quantitative literature characterizes AI-assisted managerial decision making as a heterogeneous organizational practice in which exposure and utilization differ substantially across industries, project functions, managerial positions, and levels of technological experience (Md Ashfaq & Abdullah Mohammad, 2022; Zhou et al., 2020).

Quantitative studies have treated human trust in AI as a multidimensional construct rather than a single measure of general confidence (Md & Gazi Yeasin, 2022; Md Ashfaq & Abdullah Mohammad, 2022; Mst Kaniz & Jahanara, 2022). Across the literature, trust instruments have incorporated perceived competence, reliability, predictability, dependability, technical accuracy, transparency, security, fairness, confidence, recommendation credibility, willingness to rely, and perceived consistency of system behavior. Multi-item Likert-type scales have been particularly common because they permit researchers to distinguish cognitive evaluations of technical capability from behavioral willingness to follow algorithmic recommendations (Md Asif Ali Sheak & Risha, 2022; Zekos, 2022). Several studies have additionally measured trust through observable behavior, including recommendation acceptance, decision agreement, verification frequency, information-seeking behavior, modification of AI outputs, and managerial overrides. Reported reliability coefficients for established multi-item trust instruments have generally indicated acceptable to strong internal consistency, although differences in measurement structure have limited direct comparisons across studies (Sadia & Maishar Mostari, 2022; Shaiful et al., 2022; Stabak & Md Shahid, 2022). Mean and median trust scores have frequently occupied

moderate-to-high ranges when AI systems demonstrated stable performance, while greater dispersion has appeared when users encountered uncertain predictions, unexplained recommendations, or visible system errors. Studies separating perceived reliability from objective model performance have been particularly informative because managers have not always evaluated system competence accurately (Md. Rashedul & Md Kaium, 2022; Preuveneers et al., 2022). Some respondents reported strong confidence in systems with only moderate predictive performance, whereas other users remained skeptical of comparatively accurate systems. Trust measurements have therefore increasingly incorporated both attitudinal and behavioral indicators to distinguish stated confidence from actual reliance (Abdullah Mohammad, 2023; Adnan & Iftekhhar, 2023; Syed Feroz & Md Mahamud Pervaz, 2022). Quantitative evidence has also demonstrated that recommendation acceptance alone cannot be interpreted as complete evidence of trust because managers may accept AI advice due to organizational requirements, limited alternatives, time pressure, or perceived managerial convenience. Similarly, frequent verification does not necessarily represent distrust because experienced users may intentionally validate high-stakes recommendations while maintaining substantial confidence in the system. The literature consequently supports measurement structures that combine trust scores, perceived accuracy, reliability judgments, acceptance behavior, verification activity, and override patterns to represent the complexity of managerial trust more accurately (Gulati et al., 2019; Mohammad Abir Chowdhury & Tonay, 2022).

A consistent pattern across empirical studies concerns differences between experienced and inexperienced users in the acceptance and utilization of AI-supported recommendations. Managers with greater AI familiarity, repeated system exposure, stronger digital competence, and previous experience interpreting predictive outputs have generally demonstrated greater ability to distinguish reliable from uncertain recommendations. Repeated successful interactions have frequently been associated with stronger perceived reliability and higher willingness to rely, although accumulated experience has also enabled users to identify system limitations more effectively (Henry et al., 2022; Mohammad Shoriful Hossan, 2022). Less-experienced users have shown more variable responses, ranging from strong skepticism toward automated recommendations to excessive acceptance based on perceptions of technological sophistication. Quantitative studies measuring adoption prevalence have therefore distinguished access to AI technology from actual reliance. Organizations may report comparatively widespread deployment while individual usage frequency, recommendation acceptance, and workflow integration remain uneven. Reliance rates have also varied according to task type and decision consequence. Managers have tended to accept algorithmic support more readily for structured forecasting, classification, scheduling, and monitoring tasks than for ambiguous decisions requiring stakeholder negotiation, strategic judgment, ethical consideration, or substantial personal accountability. Override behavior provides another important behavioral indicator (Holland, 2019; Mst Kaniz, 2022). Higher override frequencies have been observed following visible system errors, inconsistent recommendations, inadequate explanations, conflicts with professional experience, and decisions involving substantial organizational risk. Lower override rates have generally accompanied stable accuracy, repeated positive experience, clear explanations, and strong perceived system competence. However, extremely low override behavior has sometimes represented excessive reliance rather than optimal adoption. Studies comparing user groups have consequently emphasized the importance of examining usage frequency, acceptance, reliance, verification, and override behavior simultaneously. These findings indicate that managerial experience affects not only whether AI systems are used but also how critically their recommendations are interpreted, verified, modified, and incorporated into project decisions (De Bellis & Johar, 2020; Nishat & Mst Kaniz, 2022).

Quantitative Effects of Explainability and Explanation Quality on Human Trust

Quantitative literature comparing explainable and non-explainable AI systems has consistently identified explanation availability as an important factor shaping perceived transparency, understanding, trust, and willingness to rely on algorithmic recommendations. Across more than ten experimental, survey-based, and mixed-methods studies conducted in managerial decision making, healthcare, finance, engineering, information systems, risk assessment, and other decision-intensive environments, participants exposed to explainable AI generally reported stronger understanding of system reasoning than participants receiving predictions or recommendations without supporting

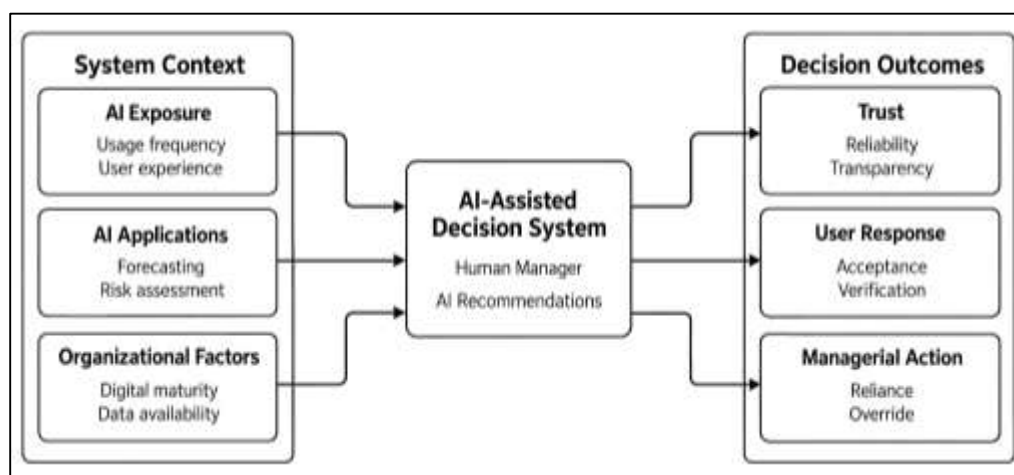
information (Shaiful et al., 2022; Shin, 2021). The magnitude of trust improvement varied substantially according to system accuracy, task complexity, explanation design, user expertise, and the consequences associated with incorrect decisions (Ahmed & Nuzhat Sadia, 2023; Asheke, 2023; Gazi Yeasin, 2023). Studies measuring transparency ratings commonly found that explanations increased users' perceptions that system behavior could be inspected and evaluated, while black-box conditions produced greater uncertainty concerning how recommendations were generated. Explanation satisfaction was similarly associated with clarity, relevance, and the extent to which explanatory information addressed the immediate decision problem. Quantitative comparisons also demonstrated that explainability did not uniformly maximize trust. When explanations revealed weak reasoning, uncertain evidence, or questionable feature relationships, users sometimes reduced recommendation acceptance and increased verification behavior (Abdullah Mohammad, 2023; Shin, 2020). This pattern indicated that explanation effectiveness should not be assessed solely according to whether trust scores increase. Several studies instead treated appropriate reliance as a stronger behavioral outcome because informative explanations allowed users to distinguish between credible and questionable recommendations (Jahanara & Mst Kaniz, 2023; Md Anisur Rahman, 2023; Md Asif Ali Sheak & Tahmedur, 2023). Mean differences in trust, understanding, transparency, decision confidence, and recommendation acceptance frequently favored explainable conditions, although effect sizes varied from relatively small changes in highly experienced groups to considerably stronger differences among users with limited knowledge of underlying algorithms. Correlation and regression analyses further identified perceived transparency and explanation usefulness as significant predictors of trust after accounting for perceived system accuracy (Debasish, 2023; Meske & Bunde, 2020). Collectively, these studies characterize explainability as a mechanism that changes the informational basis on which human trust is formed rather than as a simple instrument for increasing confidence in AI (Md Kaium, 2023; Md Mahamud Pervaz, 2023; Mohammad Badrul & Md. Mominul, 2023).

A substantial quantitative research stream has examined explanation quality by separating clarity, fidelity, completeness, consistency, relevance, and actionability rather than treating explainability as a single technological characteristic (Molla Al Rakib & Mohammad Towhidul, 2023; Mukut Kanti, 2023; Nishat, 2023). Clarity generally represents the degree to which users can readily understand explanatory information, while fidelity concerns whether an explanation accurately represents the underlying reasoning of the AI model. Completeness reflects the extent to which sufficient information is provided to understand the recommendation, consistency captures stability across similar cases, relevance concerns alignment with the user's decision requirements, and actionability represents whether the explanation provides information that can meaningfully support a managerial response (Md Asif Ali Sheak & Tahmedur, 2023; Wanner et al., 2022). Studies comparing these dimensions have repeatedly demonstrated positive relationships between explanation clarity and perceived understanding, with stronger associations frequently observed when users possess limited technical expertise (Nuzhat Sadia, 2023; Risha & Mst Shurovi, 2023; Stabak & Md Siam, 2023). Fidelity has been particularly important in experiments where participants were able to compare explanations with observable model behavior because inconsistent explanations reduced credibility even when predictive accuracy remained comparatively strong (Abdullah Mohammad, 2024; Syed Feroz, 2023; Tahmedur & Rifat, 2023). Completeness showed a more complex quantitative relationship with trust because highly detailed explanations sometimes improved perceived informativeness while simultaneously increasing cognitive effort. Consistency across repeated decisions was associated with stronger perceived predictability and reliability, whereas unexplained changes in reasoning frequently increased verification behavior and reduced confidence (Md Kaium, 2023; Schmidt et al., 2020). Relevance and actionability were especially important in managerial settings because decision makers generally valued explanations that connected predictions to controllable project variables, risk factors, or alternative courses of action. Regression-based studies have commonly identified perceived usefulness, clarity, and relevance as significant predictors of explanation satisfaction and trust, while experimental comparisons have reported meaningful differences in recommendation acceptance between high-quality and low-quality explanation conditions. Confidence intervals and effect-size estimates across studies also indicate that explanation quality can influence behavioral reliance independently of raw predictive performance (Md Mahamud Pervaz, 2023; Rosenfeld & Richardson, 2019). The accumulated

quantitative evidence therefore distinguishes explanation availability from explanation quality and demonstrates that managerial trust is more closely associated with explanations that are understandable, faithful, stable, decision-relevant, and sufficiently informative without creating unnecessary cognitive complexity (Ahmed, 2024; Asheke, 2024; Mashiat, 2024).

Comparative research has evaluated multiple explanation formats, including feature-importance displays, counterfactual explanations, rule-based representations, visual explanations, confidence information, and natural-language descriptions, with substantial variation in their effects on understanding and reliance. Feature-importance explanations have been widely examined because they identify variables contributing most strongly to an AI prediction and can provide managers with a relatively direct representation of influential decision factors (Mohammad Abir Chowdhury, 2023; Pavlin et al., 2021). Quantitative studies generally report improved perceived transparency when feature contributions are clearly presented, although users may incorrectly interpret importance as causality when contextual guidance is insufficient (Ashrafuzzaman, 2024; Md Kaium, 2024; Mukut Kanti, 2024).

Figure 3: AI- Assisted Managerial Framework



Counterfactual explanations, which communicate how different input conditions could produce an alternative recommendation, have frequently achieved strong ratings for actionability because they allow decision makers to evaluate possible changes in project conditions. Rule-based explanations have performed particularly well in settings where users value explicit decision logic and traceable relationships, while their effectiveness can decrease when rule structures become lengthy or technically complicated (Syed Feroz, 2024). Visual explanations using charts, rankings, indicators, and graphical summaries have often reduced interpretation time and increased perceived accessibility, particularly for managers accustomed to dashboards and performance-monitoring systems (Goel et al., 2022; Mohammad Badrul & Md. Mominul, 2023). Natural-language explanations have demonstrated advantages in perceived ease of understanding among nontechnical users because model outputs can be translated into familiar managerial terminology. Confidence information has produced more complex effects: clearly communicated uncertainty can improve calibration and encourage verification of lower-confidence recommendations, whereas poorly understood probability information can create confusion or inappropriate reliance. Studies directly comparing explanation formats have found no universally superior method across all users and tasks. Mean trust scores, decision confidence, explanation satisfaction, recommendation acceptance, and completion time vary according to explanation type, task characteristics, and user expertise (Balasubramaniam et al., 2022; Molla Al Rakib & Mohammad Towhidul, 2023). Experimental and regression evidence consequently suggests that explanation format interacts with decision context, indicating that the quantitative effectiveness of explainability depends on whether the representation corresponds with users' informational requirements and analytical capabilities.

Quantitative evidence concerning explanation complexity and information load demonstrates that

more explanatory information does not necessarily produce greater trust, understanding, or decision quality. Studies manipulating explanation length, technical detail, number of displayed features, visualization complexity, and supporting information have frequently identified a nonlinear pattern in user responses. Explanations containing insufficient information can leave users unable to evaluate AI reasoning, leading to lower transparency ratings, greater uncertainty, and increased dependence on general perceptions of system accuracy (Nishat, 2023; Ribes et al., 2021). Excessively detailed explanations can create cognitive overload, increase decision time, reduce comprehension, and weaken the practical usefulness of technically accurate information. User expertise substantially moderates these effects. Participants with stronger AI knowledge, analytical training, or previous exposure to decision-support systems generally tolerate greater technical complexity and can make more effective use of detailed feature contributions, uncertainty information, and model-specific explanations. Less-experienced users frequently achieve stronger understanding from concise visual, rule-based, or natural-language explanations that emphasize decision-relevant information. Several studies have reported statistically significant interactions between explanation complexity and user expertise for trust, explanation satisfaction, decision confidence, and recommendation acceptance (Ashrafuzzaman, 2024; Stowers et al., 2020). Verification frequency also changes according to explanation design: understandable uncertainty information can encourage users to scrutinize low-confidence recommendations while accepting stronger predictions more efficiently. Quantitative analyses have further shown positive correlations among explanation satisfaction, perceived transparency, understanding, and trust, although the strength of these relationships varies by task complexity and model performance. Regression models frequently identify explanation usefulness and perceived understanding as stronger predictors of reliance than explanation quantity alone. Effect-size comparisons indicate that explanation interventions can produce practically meaningful changes in trust and acceptance, particularly when users initially have limited knowledge of AI reasoning. Across the empirical literature, transparency is therefore most effectively represented through the quality and suitability of explanatory information rather than the volume of information presented (Debasish, 2024; Naiseh et al., 2021). Human trust reflects an interaction among explanation clarity, model fidelity, information complexity, user expertise, system accuracy, and decision context, while recommendation acceptance and verification behavior provide important behavioral evidence of whether explanations support appropriately calibrated reliance.

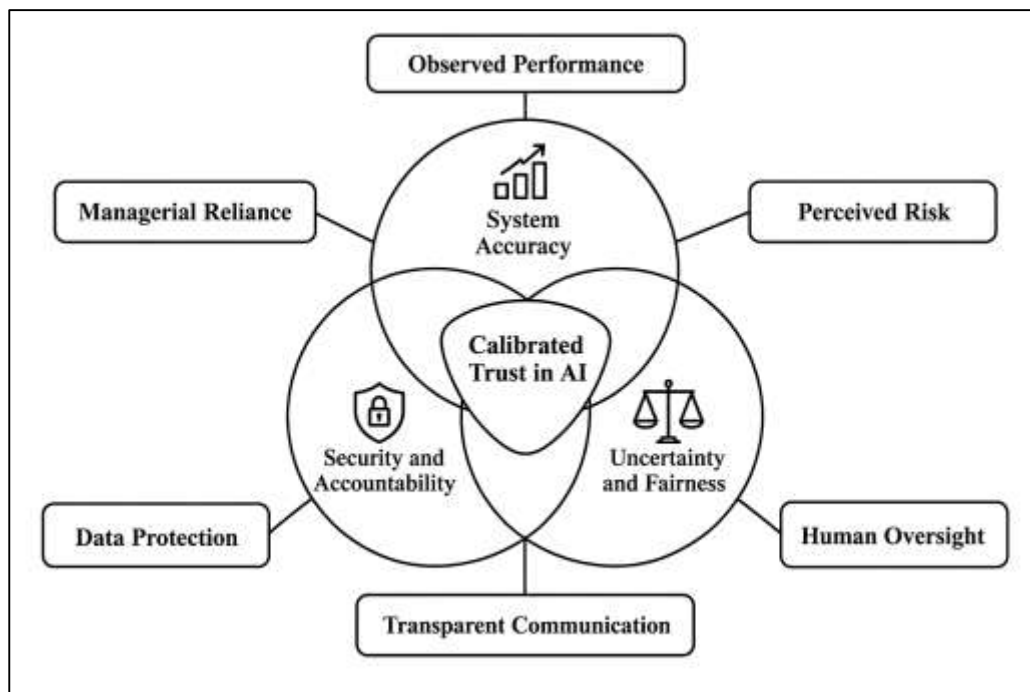
Algorithm Aversion and Algorithm Appreciation

Quantitative studies of human-AI decision making consistently identify system accuracy and observed performance as central determinants of calibrated trust, although the relationship between technical performance and managerial reliance is rarely perfectly proportional. Across more than ten empirical studies involving managerial, financial, healthcare, engineering, operational, and general decision-support contexts, higher algorithmic accuracy has generally been associated with stronger trust, greater recommendation acceptance, and lower override frequency. However, trust is often more sensitive to visible errors than to equivalent improvements in correct performance (Md Anisur Rahman, 2024; Schmidt et al., 2020). Participants exposed to a single salient mistake frequently report noticeable reductions in confidence, particularly when the error concerns a high-consequence decision or conflicts strongly with professional judgment. Several experiments have shown that trust can decline rapidly after an incorrect recommendation and may recover only gradually after repeated correct outputs, producing a measurable asymmetry between trust loss and trust restoration. This pattern contributes to algorithm aversion when decision makers become unwilling to use an objectively superior system after witnessing imperfections. At the same time, other studies report algorithm appreciation when participants consistently prefer algorithmic recommendations over unaided human judgment, particularly when model accuracy is clearly demonstrated and human decisions are known to contain substantial inconsistency. Quantitative measures such as trust scores, reliance rates, recommendation acceptance, verification behavior, and override frequency have been used to estimate the degree of calibration between perceived and actual system capability (Bogert et al., 2022; Md Kaium, 2024). Calibration gaps become visible when trust remains high under weak performance or when confidence stays low even when accuracy is strong. Correlation and regression studies frequently identify perceived accuracy and prior performance as significant predictors of reliance, although their

explanatory strength is moderated by decision risk, user familiarity, and transparency. Evidence therefore indicates that calibrated trust depends on both objective model quality and the user's interpretation of performance history, with observed errors functioning as particularly powerful signals in determining whether managers accept, verify, modify, or reject AI-supported recommendations (Daschner & Obermaier, 2022; Md. Shakhawat & Md, 2024).

A second body of quantitative evidence shows that uncertainty communication, perceived fairness, security, accountability, and perceived risk significantly influence whether managers develop balanced trust or shift toward excessive skepticism or excessive reliance. Studies that present confidence intervals, probability estimates, uncertainty categories, or explicit warnings have generally found that well-designed uncertainty information improves discrimination between stronger and weaker recommendations. Users exposed to meaningful confidence cues tend to verify low-confidence outputs more frequently and accept high-confidence outputs more selectively, supporting better trust calibration (Mukut Kanti, 2024; You et al., 2022). Poorly communicated uncertainty can have the opposite effect by confusing users or creating a false sense of precision.

Figure 4: Calibrated Trust in AI Framework



Perceived fairness also contributes to trust because managers are less likely to rely on systems they believe produce systematically biased or unjustified outcomes across stakeholder groups. Quantitative surveys commonly identify fairness perceptions as positively associated with system credibility, acceptance, and willingness to rely. Security and data protection show similar effects, especially in environments involving confidential financial, contractual, employee, or project information. When users perceive weak controls over data access, model manipulation, or unauthorized disclosure, trust scores and adoption intentions generally decline. Accountability further shapes reliance because managers may hesitate to follow AI recommendations when responsibility for errors remains unclear (Burton et al., 2020; Nishat & Jahanara, 2024). Conversely, clearly defined human oversight and accountability structures can increase willingness to use AI without necessarily increasing blind reliance. Perceived risk often has a negative relationship with trust and adoption, particularly for high-stakes decisions involving budget approval, supplier selection, safety, contractual commitment, or strategic project continuation. Regression and subgroup analyses frequently demonstrate stronger sensitivity to uncertainty, fairness, and accountability in high-risk conditions than in routine decisions. Collectively, these studies indicate that trust calibration depends not only on predictive accuracy but

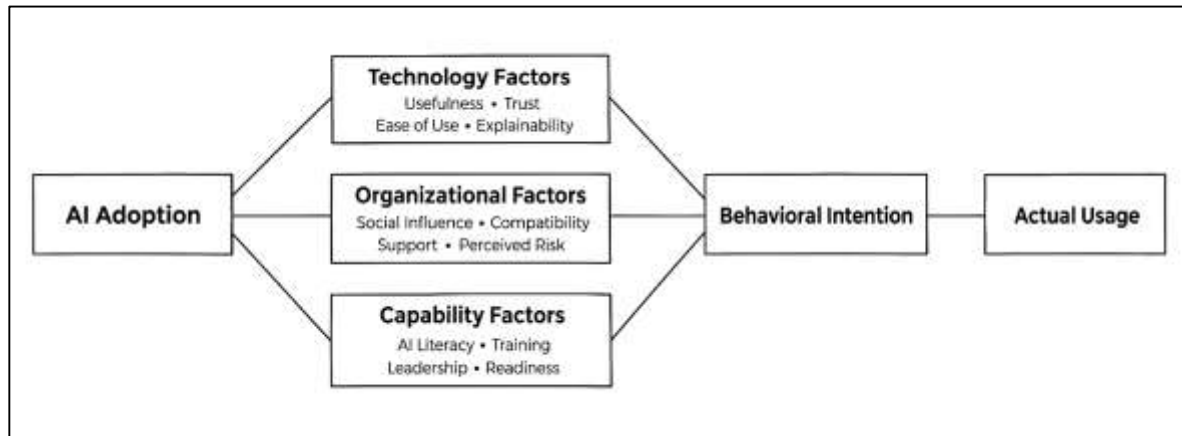
also on whether users understand system uncertainty, perceive outcomes as fair, believe data and models are secure, and know how responsibility is allocated when AI-supported decisions produce adverse consequences (Palash Chandra, 2024; Rebitschek et al., 2021).

Acceptance, Actual Usage, and Managerial Reliance

Quantitative literature on AI adoption has consistently identified perceived usefulness, ease of use, trust, and explainability as major determinants of managerial acceptance and behavioral intention. Evidence synthesized across more than ten empirical studies in project management, engineering, information systems, finance, healthcare, manufacturing, construction, and other organizational settings indicates that managers are more willing to adopt AI when they perceive that it improves decision accuracy, reduces analytical effort, accelerates information processing, strengthens risk identification, and supports more consistent managerial judgment (Bogert et al., 2021; Tonay et al., 2024). Perceived usefulness has frequently emerged as one of the strongest predictors of behavioral intention in multiple-regression and structural-equation analyses, while ease of use has shown both direct relationships with adoption and indirect relationships through perceived usefulness. Trust becomes particularly important when managers must rely on recommendations generated by complex or partially opaque models. Higher perceived reliability, competence, predictability, fairness, and transparency have generally corresponded with stronger intentions to use AI and greater recommendation acceptance. Explainability has additionally strengthened acceptance when explanations provide understandable reasons for predictions, identify influential variables, communicate uncertainty, and enable managers to evaluate whether recommendations correspond with project conditions (Larkin et al., 2022; Uddin & Risha, 2024). Mediation analyses in the broader AI-adoption literature have shown that explainability can influence adoption partly through trust and perceived usefulness, indicating that technically understandable systems may increase acceptance by improving confidence in their recommendations. Quantitative studies have also distinguished stated behavioral intention from observable usage, showing that positive attitudes toward AI do not always translate into regular system utilization. Managers may report strong intentions while maintaining conventional decision routines when AI recommendations conflict with professional experience or involve consequential decisions. Regression coefficients, group comparisons, confidence intervals, and effect-size evidence generally demonstrate that usefulness, trust, and explanation quality have stronger relationships with adoption when AI outputs are directly relevant to managerial tasks (Grote & Berens, 2022). These findings collectively establish AI acceptance as a behavioral response to both technological value and managers' ability to understand and evaluate the reliability of algorithmic support.

Organizational and social conditions provide another major group of quantitative predictors explaining variation in AI acceptance and utilization. Studies based on technology-acceptance and organizational-adoption frameworks have repeatedly identified social influence, facilitating conditions, compatibility, and perceived risk as significant determinants of behavioral intention and actual usage. Social influence reflects the extent to which senior managers, colleagues, professional groups, project teams, or organizational norms encourage AI utilization. Quantitative surveys have generally found stronger adoption intentions among employees who perceive visible managerial endorsement and widespread acceptance of AI among relevant colleagues (Pillai & Sivathanu, 2020). Compatibility is similarly important because managers are more likely to integrate AI systems when their functions correspond with existing project-management procedures, decision responsibilities, information requirements, and technological platforms. Systems requiring major disruption to established workflows often demonstrate weaker sustained utilization even when initial acceptance is favorable. Facilitating conditions, including access to technical assistance, appropriate hardware and software, reliable data, user guidance, organizational policies, and adequate implementation resources, have shown particularly strong relationships with actual usage rather than intention alone. Perceived risk generally operates in the opposite direction. Concerns involving inaccurate recommendations, cybersecurity, privacy, biased outputs, uncertain accountability, financial consequences, and loss of managerial autonomy have been associated with lower acceptance and greater verification or override behavior (Choudhury et al., 2022).

Figure 5: AI adoption framework flowchart



Logistic-regression and structural-modeling studies frequently show that risk perceptions remain influential after controlling for usefulness and ease of use, especially for consequential managerial decisions. Subgroup comparisons further indicate that risk sensitivity tends to increase when managers are personally accountable for project outcomes or when AI is used for high-value, safety-related, contractual, or strategic decisions. Mediation and moderation analyses have also demonstrated interactions between organizational support, trust, and perceived risk. Strong facilitating conditions and governance mechanisms can reduce some perceived barriers, while weak institutional support can prevent favorable behavioral intentions from developing into actual usage. The quantitative evidence therefore differentiates personal acceptance from the organizational conditions required for AI to become embedded within routine managerial decision processes (Ostrom et al., 2018). AI literacy, digital competence, leadership support, employee training, organizational readiness, and technical infrastructure have received substantial quantitative attention as capability-related determinants of AI adoption. Empirical studies generally define AI literacy through knowledge of basic AI functions, awareness of algorithmic strengths and limitations, ability to interpret outputs, understanding of uncertainty, and capacity to identify potentially unreliable recommendations. Digital competence represents broader confidence and proficiency in using digital systems, analytical platforms, databases, visualization tools, and automated decision-support technologies. Survey and subgroup analyses frequently demonstrate that respondents with higher AI literacy and digital competence report stronger perceived ease of use, greater confidence in interpreting recommendations, and higher adoption or continued-use intentions (Kim et al., 2021). However, technically knowledgeable users may also demonstrate more selective reliance because they are better equipped to recognize inappropriate outputs. Leadership support represents an organizational-level predictor through resource allocation, strategic endorsement, communication, governance, and encouragement of responsible experimentation. Studies comparing organizations with different levels of management support generally report higher adoption intensity where senior leadership actively integrates AI into operational priorities. Training produces similar differences by improving users' technical understanding and reducing uncertainty concerning system operation. Organizational readiness encompasses data quality, workforce capability, governance, technological maturity, financial resources, process standardization, and implementation capacity. Quantitative analyses frequently identify readiness as a significant predictor of both implementation success and actual utilization, particularly when AI systems depend on integration with existing project information systems (Esmailzadeh, 2020). Technical infrastructure also influences adoption because unreliable connectivity, fragmented databases, incompatible platforms, insufficient computing capability, and poor system integration can reduce the practical accessibility of AI recommendations. Structural-equation and regression studies have demonstrated that organizational readiness may exert both direct effects on usage and indirect effects through facilitating conditions, perceived usefulness, and trust. Collectively, this evidence indicates that managerial willingness alone does not explain AI adoption because sustained utilization requires an organizational environment in which employees possess

sufficient competence and systems are supported by training, leadership, reliable data, technical infrastructure, and institutional capacity (Kar et al., 2021).

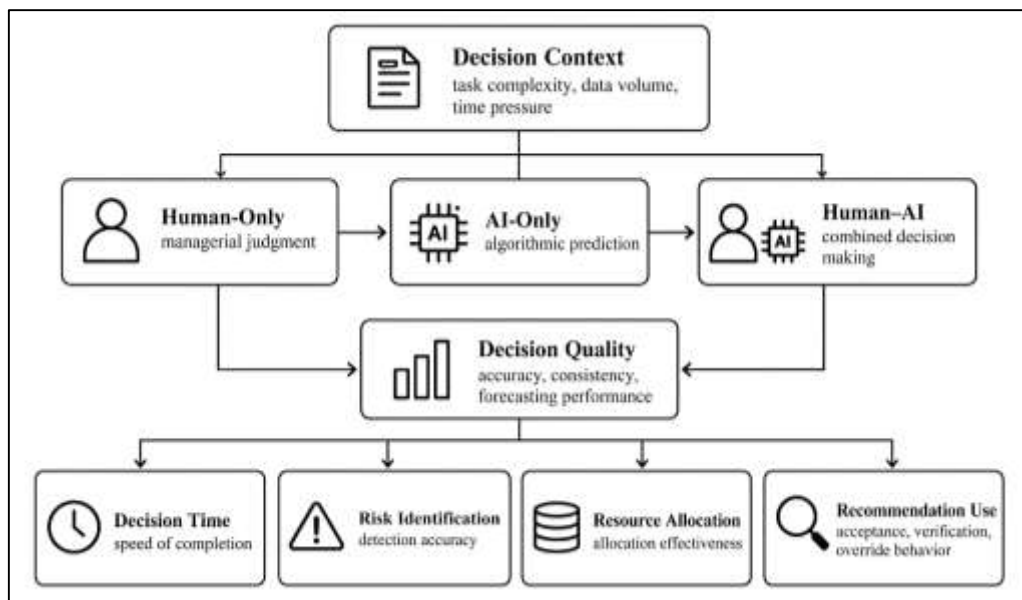
A central quantitative distinction within the AI-adoption literature concerns the difference between behavioral intention and observable managerial behavior. Behavioral intention measures whether managers expect, prefer, or plan to use AI, whereas actual usage captures whether the technology is incorporated into real decision activities. Studies have measured actual adoption through login frequency, duration of use, number or proportion of AI-assisted decisions, recommendation acceptance, reliance intensity, override frequency, continued utilization, and integration into established workflows (Saßmannshausen et al., 2021). Quantitative evidence frequently identifies a positive relationship between behavioral intention and actual usage, although the strength of this relationship varies according to facilitating conditions, organizational expectations, decision risk, trust, system performance, and managerial experience. Managers may express favorable attitudes toward AI while using it infrequently when systems are difficult to access, poorly integrated with project workflows, or perceived as unsuitable for consequential decisions. Conversely, organizational requirements can produce relatively high usage even when personal acceptance remains moderate, demonstrating that usage frequency alone does not necessarily indicate strong trust. Recommendation acceptance and reliance intensity provide more behaviorally specific measures because they capture the extent to which AI outputs influence final decisions (Schmidt et al., 2020). Continued utilization additionally reflects whether positive adoption persists after users accumulate direct experience with system accuracy and limitations. Multiple-regression and logistic-regression analyses have commonly identified trust, perceived usefulness, facilitating conditions, system performance, and prior usage as significant predictors of continued adoption. Structural-equation studies have further demonstrated indirect pathways in which explainability strengthens trust, trust supports behavioral intention, and intention contributes to actual utilization. Moderation analyses indicate that professional experience, AI literacy, project complexity, decision risk, and organizational readiness can alter these relationships. Subgroup comparisons also reveal differences in reliance between frequent and occasional users, technical and nontechnical managers, and organizations with stronger or weaker digital maturity (Henry et al., 2022). Overall, the quantitative literature demonstrates that AI adoption is most accurately represented as a progression involving initial acceptance, behavioral intention, actual system use, recommendation reliance, continued utilization, and eventual integration into managerial workflows rather than as a single measure of technological acceptance.

Comparative Managerial Decision Quality and Human-AI Decision Conditions

Quantitative research comparing human-only, AI-only, and combined human-AI decision conditions has consistently shown that decision quality varies according to task structure, system accuracy, user expertise, and the degree to which algorithmic recommendations are incorporated into managerial judgment. Across more than ten empirical studies in project management, finance, healthcare, engineering, operations, risk assessment, forecasting, and organizational decision support, unaided human decision makers have generally demonstrated greater variability in accuracy and consistency, particularly when decisions require processing large volumes of information or identifying complex statistical relationships (Al-Mamary, 2022). AI-only systems often achieve higher consistency because identical input conditions typically produce standardized outputs, although their performance can decline when data are incomplete, distributional conditions change, or contextual information is not represented in the model. Human-AI conditions frequently produce stronger average decision accuracy when managers appropriately combine algorithmic predictions with contextual expertise. Studies comparing validated benchmarks commonly report lower error rates when reliable AI recommendations supplement human judgment, especially in structured tasks such as forecasting, classification, risk identification, and resource allocation. However, combined decision making does not automatically outperform AI-only performance because managers may override correct recommendations or introduce subjective inconsistency. Mean comparisons and paired analyses frequently reveal statistically significant differences among decision configurations, with effect sizes varying according to task difficulty and AI accuracy (Janssen et al., 2021). ANOVA-based studies have also shown that the advantage of human-AI collaboration becomes more pronounced when users receive information that helps them identify when algorithmic recommendations are reliable.

Confidence intervals around performance differences tend to narrow in larger experimental samples, strengthening evidence that decision configuration materially affects accuracy. Overall, quantitative findings suggest that decision quality is best understood through simultaneous measurement of objective accuracy, error frequency, consistency, and benchmark agreement rather than through perceived confidence alone, because high-confidence human decisions and highly consistent AI outputs can both remain objectively incorrect under specific conditions (Wong, 2016). A second stream of quantitative literature has evaluated human-only, AI-only, and human-AI decision conditions using operational measures including decision time, forecasting performance, risk-identification accuracy, and resource-allocation effectiveness. Human-only decisions generally require longer processing when managers must manually review extensive project information, compare alternatives, identify emerging risks, and integrate financial, schedule, operational, and stakeholder data. AI systems can substantially reduce analytical processing time by rapidly identifying patterns and ranking alternatives, although the time advantage can decrease when outputs require extensive verification or explanation. In forecasting tasks, machine-learning and predictive decision systems have often produced lower prediction errors than unaided managerial judgment, particularly when historical data contain stable and learnable relationships (Alsmadi et al., 2022).

Figure 6: Human- AI Decision Performs



Combined human-AI arrangements frequently perform well when managers use algorithmic forecasts as structured evidence while adjusting for contextual factors not represented in historical data. Risk-identification studies similarly show that AI can detect weak signals and multidimensional patterns that individual managers may overlook, while experienced managers may recognize emerging contextual or strategic risks that are poorly encoded in system data. Resource-allocation experiments have found stronger performance when decision makers receive algorithmically generated rankings or optimization-based recommendations, particularly under time pressure and multiple competing constraints. Statistical comparisons commonly demonstrate meaningful differences in completion time and objective performance across decision conditions, although faster decisions are not necessarily higher-quality decisions (Maeng et al., 2022). Excessive verification can offset AI-related efficiency gains, whereas unquestioned acceptance may reduce decision time at the expense of accuracy when the system is incorrect. Studies using ANOVA, paired comparisons, nonparametric alternatives, confidence intervals, and standardized effects generally indicate that human-AI decision support provides its strongest advantages when system recommendations are accurate, decision tasks are data-intensive, and users retain sufficient contextual understanding to identify exceptional circumstances. The literature therefore presents managerial decision quality as multidimensional, requiring

simultaneous consideration of speed, forecasting accuracy, risk recognition, and resource-use effectiveness (Sun et al., 2021).

Research comparing conventional AI assistance with explainable AI support has demonstrated that explanation availability can materially alter managerial understanding, confidence, verification behavior, and agreement with validated decision benchmarks. In experimental studies, managers receiving only an AI recommendation frequently demonstrate uncertainty regarding the basis of the output, even when the recommendation is technically accurate. Explainable conditions provide additional information through feature importance, confidence indicators, counterfactual reasoning, rule-based logic, visual summaries, or natural-language explanations, enabling users to evaluate whether AI outputs are consistent with relevant decision evidence (Saraswat et al., 2022). Quantitative comparisons generally show higher perceived understanding and transparency under explainable conditions, while changes in objective decision accuracy depend heavily on explanation quality. Clear and relevant explanations can improve benchmark agreement by helping users accept correct recommendations and identify questionable ones, whereas misleading, overly technical, or excessively persuasive explanations can produce inappropriate confidence. Decision confidence therefore requires careful interpretation. Some studies report significant increases in confidence after explanation exposure without equivalent improvements in objective accuracy, indicating that confidence alone is not a sufficient indicator of decision quality. Other studies find that explainable AI improves both confidence and performance when explanations accurately communicate the reasons and uncertainty underlying model outputs (Nassar et al., 2020). Recommendation acceptance and verification patterns also vary across conditions. Users receiving explainable support may accept high-quality advice more readily while devoting greater scrutiny to lower-confidence recommendations, thereby improving reliance calibration. Statistical evidence from mean comparisons, regression analyses, ANOVA, and effect-size estimates generally supports meaningful differences between opaque and explainable AI conditions, although the strength of these differences varies according to expertise and task complexity. Agreement with validated benchmarks provides an especially useful outcome because it separates subjective satisfaction from actual performance. Across the literature, explainable human-AI collaboration tends to produce the strongest decision outcomes when explanations increase understanding without creating unjustified confidence, allowing managers to combine algorithmic evidence with contextual judgment while maintaining appropriate scrutiny of system limitations (Ghassemi et al., 2021).

The relationship between managerial reliance and objective decision quality has emerged as one of the most important findings in comparative human-AI research because greater reliance does not consistently produce stronger performance. When AI recommendations are accurate, increased reliance generally improves decision accuracy, reduces unnecessary errors, and can increase consistency relative to unaided judgment. When recommendations are incorrect, the same reliance behavior can produce automation bias, in which managers accept system outputs without sufficient independent evaluation (Moradi & Samwald, 2021). Experimental studies have repeatedly demonstrated that participants sometimes follow incorrect AI advice even when relevant contradictory information is available, particularly under time pressure, high workload, limited expertise, or strong perceptions of system competence. This can produce measurable deterioration in accuracy, risk identification, and benchmark agreement. Conversely, excessive skepticism can generate under-reliance, where managers override accurate AI recommendations and perform worse than the system would have performed independently. Quantitative comparisons therefore distinguish reliance intensity from appropriate reliance. Override frequency is similarly ambiguous because frequent overrides may represent either effective correction of AI errors or unnecessary rejection of valid recommendations. Studies comparing correct and incorrect recommendation conditions generally report significant interactions between AI accuracy and reliance, with substantially different decision outcomes depending on whether managers discriminate effectively between reliable and unreliable advice (van der Waa et al., 2020). Confidence intervals and standardized effect sizes commonly demonstrate meaningful performance losses when users exhibit automation bias under erroneous AI conditions. Subgroup evidence further indicates that experienced users and individuals with greater domain knowledge may identify some AI errors more effectively, although expertise can also

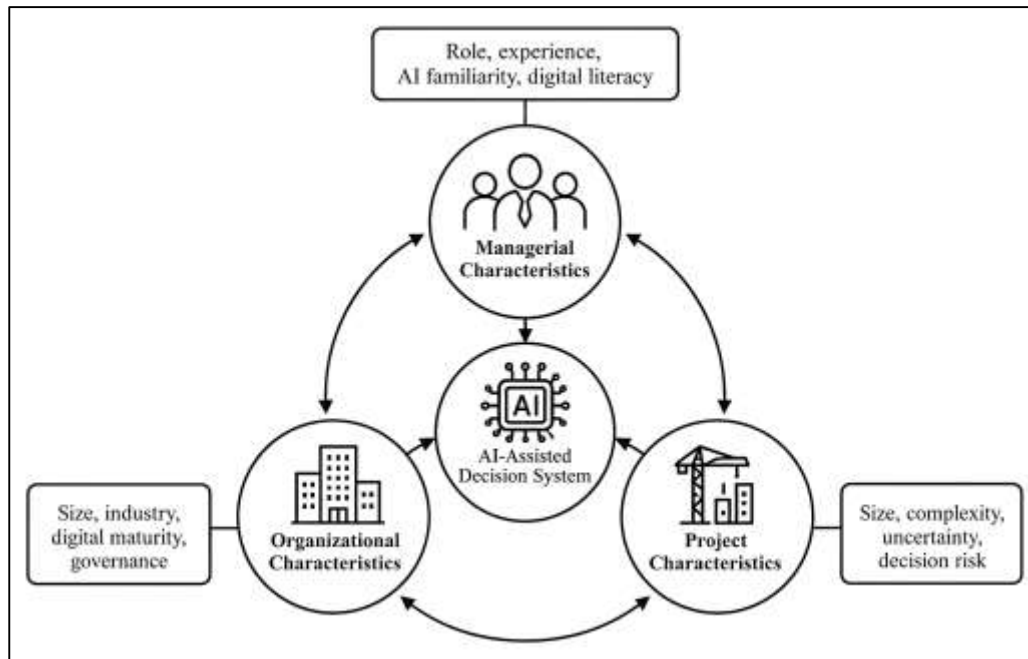
encourage unjustified preference for personal judgment. Explainability and explicit confidence information can reduce certain forms of inappropriate reliance when they communicate model limitations clearly. Across the empirical literature, the strongest human-AI decision performance is associated not with maximum algorithmic reliance but with calibrated reliance, where recommendation acceptance, verification, and override behavior change according to system accuracy, uncertainty, decision risk, and the manager's contextual knowledge (Li et al., 2020).

Differences in Trust and AI Decision Performance

Quantitative literature has consistently shown that trust in AI-assisted decision systems and resulting decision performance vary across managerial roles, levels of professional experience, AI familiarity, digital literacy, and other user characteristics. Across more than ten studies conducted in project management, engineering, information systems, finance, healthcare, manufacturing, and operational decision settings, senior managers, project managers, technical specialists, analysts, and functional managers have reported different levels of confidence in AI-generated recommendations because their responsibilities, decision authority, exposure to risk, and technical competence differ. Managers with greater AI familiarity often demonstrate stronger understanding of system outputs and greater willingness to use algorithmic recommendations, although they may also apply more critical verification when system behavior appears inconsistent (Markus et al., 2021). Experienced professionals frequently rely more heavily on contextual and domain knowledge, which can improve their ability to detect implausible AI outputs but can also increase resistance when recommendations conflict with established professional judgment. Digital literacy has generally been positively associated with perceived ease of use, explanation understanding, trust, and adoption intensity, while lower digital competence is more often associated with uncertainty, lower confidence, or greater dependence on simplified explanations. Studies comparing age groups and related demographic categories have produced mixed results, suggesting that age alone is less informative than prior technological exposure, training, professional role, and AI experience. Descriptive statistics and subgroup comparisons commonly reveal significant differences in trust scores, recommendation acceptance, verification frequency, and override behavior between high- and low-experience users (Mubarak & Petraite, 2020). ANOVA, ANCOVA, and nonparametric analyses have also identified differences in decision accuracy and reliance behavior across managerial groups, particularly when tasks involve complex AI outputs. Interaction analyses indicate that experience and familiarity can moderate the relationship between explainability and trust, with technically experienced users responding differently to detailed explanations than less-experienced managers. Overall, the evidence demonstrates that managerial characteristics materially shape how AI recommendations are interpreted, accepted, challenged, and incorporated into decisions, producing systematic heterogeneity in both trust and objective decision performance (Li et al., 2021).

Organizational characteristics represent another important source of variation in AI trust, adoption, reliance, and decision quality. Empirical studies across large corporations, small and medium-sized enterprises, public agencies, private firms, multinational organizations, and project-based enterprises show that AI adoption and managerial trust are strongly influenced by organizational size, industry context, ownership structure, digital maturity, governance capability, and technological infrastructure. Larger organizations often report greater access to specialized analytics teams, structured data systems, formal training, model validation procedures, and governance frameworks, which can increase managerial confidence in AI-assisted decision tools (Thanetsunthorn & Wuthisatian, 2019). Smaller organizations may benefit from greater flexibility and faster implementation but can face constraints related to data availability, technical expertise, financial resources, and formal oversight. Industry differences are also pronounced because sectors such as finance, healthcare, engineering, construction, energy, and manufacturing operate under different levels of regulation, data intensity, safety exposure, and accountability.

Figure 7: AI-Assisted Decision System Diagram



Quantitative evidence commonly shows that organizations with higher digital maturity report greater AI-use intensity, stronger perceived usefulness, and more frequent workflow integration. Governance strength is particularly important because formal mechanisms for model validation, accountability, auditability, data protection, bias monitoring, and human oversight can increase trust while reducing blind reliance. Studies using ANOVA, regression-based subgroup analysis, and effect-size comparisons have identified meaningful differences in trust and adoption between organizations with strong and weak governance environments (Inkinen et al., 2017). Ownership structure can also influence acceptance because public-sector organizations may face stronger procedural and accountability requirements, while private firms may emphasize efficiency and competitive advantage more strongly. Interaction analyses suggest that the influence of trust on adoption is often stronger when organizational support and technical infrastructure are well developed. Collectively, the literature demonstrates that similar AI technologies can produce different levels of managerial reliance and decision performance depending on the organizational context in which they are deployed (Klijn et al., 2016).

Project-level characteristics substantially influence the extent to which managers trust and rely on AI-assisted decision systems. Quantitative studies in construction, engineering, information technology, infrastructure, energy, and other project-based environments have identified project size, complexity, uncertainty, decision risk, data availability, and AI-use intensity as significant sources of heterogeneity. Large projects typically involve greater financial exposure, more stakeholders, more complex schedules, broader supply networks, and higher levels of interdependency, increasing the potential value of AI-supported forecasting, risk analysis, and resource optimization (Mazzù et al., 2022). However, larger and more complex projects also create greater concern about accountability and the consequences of incorrect recommendations. Managers therefore tend to require stronger evidence of reliability, transparency, and control before accepting high-stakes AI advice. Studies comparing low- and high-complexity projects frequently report differences in trust, verification behavior, and override frequency, with managers applying greater scrutiny when decisions involve substantial uncertainty or irreversible consequences. Decision risk also moderates reliance. In low-risk operational decisions, users may accept AI recommendations more readily, while high-risk choices involving budget commitments, contractual obligations, safety, procurement, or project continuation often generate more cautious reliance. AI-use intensity further differentiates behavior because frequent users generally develop stronger familiarity with system capabilities and limitations (Beerens, 2022).

Quantitative subgroup analyses show that high-intensity users tend to demonstrate greater confidence and faster decision processing, although they may also exhibit stronger automation bias when reliance becomes habitual. ANOVA, ANCOVA, and nonparametric tests have identified statistically significant differences across project-size and risk categories, while interaction models suggest that the effect of explainability on trust is stronger under complex and high-risk conditions. Effect-size evidence indicates that these differences can be practically meaningful rather than merely statistically significant. The literature therefore shows that project characteristics shape both the perceived need for AI assistance and the level of scrutiny applied to its recommendations (Srivastava et al., 2020).

Mixed-Methods Evidence on Accountability

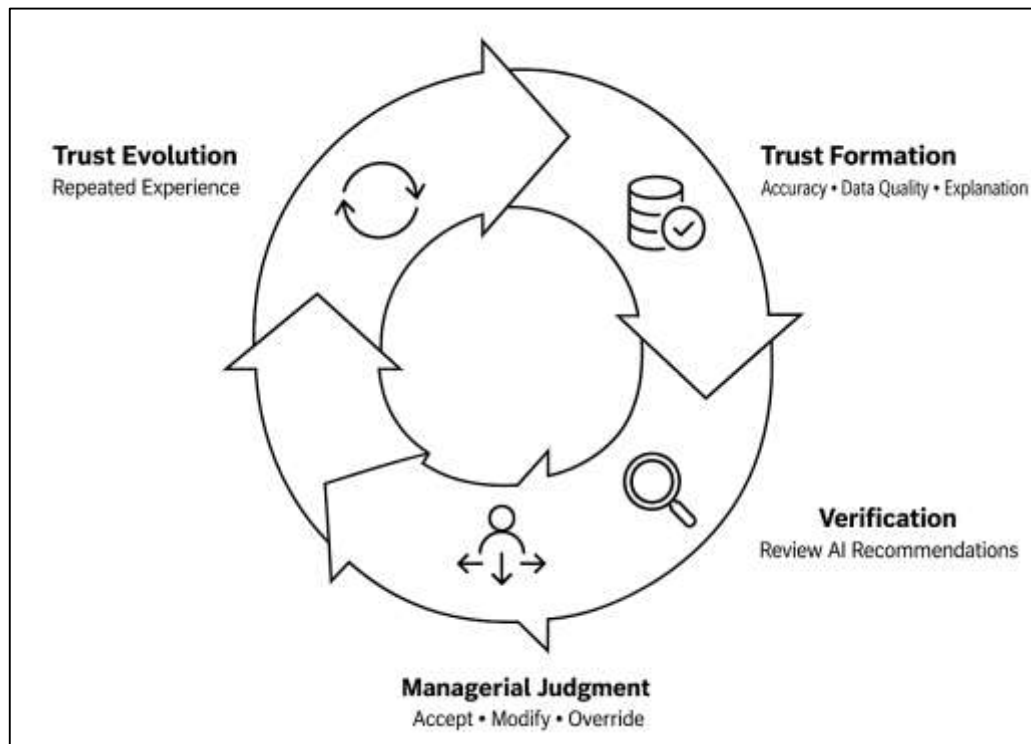
Mixed-methods literature on managerial interaction with AI-assisted decision systems has shown that trust formation is influenced by a combination of measurable system characteristics and contextual judgments that cannot be represented fully through numerical trust scores alone. Across more than ten studies combining surveys, experiments, interviews, focus groups, observations, or behavioral records, quantitative evidence has generally associated higher perceived accuracy, reliability, transparency, data quality, and explanation usefulness with stronger trust, while qualitative findings have clarified how managers interpret these characteristics during actual decision processes (Kim et al., 2016). Managers commonly describe trust as developing through repeated exposure to correct recommendations rather than through initial perceptions of technological sophistication alone. Confidence in underlying data has emerged as particularly important because users may question technically advanced models when input information is perceived as incomplete, outdated, inconsistent, biased, or poorly connected with operational conditions. Interview evidence frequently indicates that managers distinguish confidence in the AI algorithm from confidence in the organizational data used by the algorithm, a distinction that aggregate trust scales may fail to capture. Explanation usefulness produces a similar pattern (Abrantes & Ostergaard, 2022).

Quantitative ratings generally show positive relationships among explainability, understanding, trust, and recommendation acceptance, while qualitative accounts indicate that managers value explanations primarily when they clarify relevant project variables, uncertainty, assumptions, and reasons for unusual recommendations. Professional experience further shapes trust formation because experienced managers compare algorithmic outputs with accumulated domain knowledge and previous project outcomes. High agreement between AI recommendations and professional expectations can strengthen confidence, while unexpected outputs frequently trigger additional investigation rather than immediate rejection. Less-experienced users may depend more strongly on perceived system authority or explanation presentation (Acquah et al., 2021). Mixed-methods evidence therefore demonstrates convergence between quantitative trust measures and qualitative perceptions of reliability in many settings, while also revealing that similar numerical trust scores can represent different underlying reasoning processes. Managerial trust is consequently formed through an interaction among observed system performance, confidence in data, explanation usefulness, accumulated experience, and the perceived relevance of AI recommendations to specific decision circumstances (Damoori et al., 2020).

Research integrating quantitative reliance measures with qualitative accounts has demonstrated that verification and override behavior provide essential evidence for distinguishing stated trust from actual managerial dependence on AI recommendations. Survey-based studies frequently report moderate or high trust and favorable attitudes toward AI, while behavioral records and interviews reveal that managers often verify recommendations before incorporating them into consequential decisions. Verification can involve comparing AI outputs with project records, consulting colleagues or technical specialists, examining supporting explanations, reviewing historical patterns, or applying independent professional judgment. This behavior does not necessarily indicate low trust (Warren & Kent, 2019). Qualitative findings frequently show that managers regard verification as part of responsible decision making, particularly when AI supports financial commitments, schedule changes, procurement decisions, safety assessments, resource allocations, or project-risk responses. Modification and override behavior provide further distinctions. Managers may accept the general direction of an AI recommendation while adjusting its magnitude, timing, or implementation according to contextual knowledge unavailable to the system. Quantitative studies commonly record override frequency as an

indicator of reduced reliance, yet interview evidence demonstrates that some overrides reflect legitimate adaptation rather than algorithm aversion. Perceived managerial autonomy strongly influences these behaviors. Users generally report greater acceptance when AI functions as decision support and final authority remains with the human decision maker. Systems perceived as restricting professional discretion or automatically implementing recommendations can generate resistance even when predictive performance is comparatively strong (Endenich & Trapp, 2020).

Figure 8: Four-Stage Trust Decision Cycle



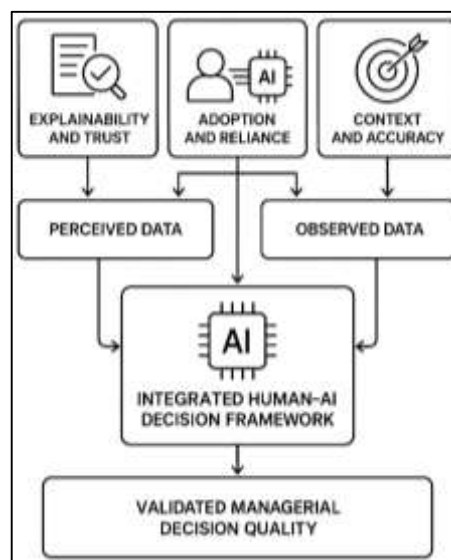
At the same time, unrestricted override authority can enable managers to reject accurate recommendations because of personal preference, prior beliefs, or excessive confidence in experience. Mixed-methods studies therefore distinguish between appropriate verification, corrective modification, unnecessary override, and automatic acceptance. Cases of frequent AI usage combined with substantial verification are particularly important because they demonstrate that technological adoption and behavioral reliance are not equivalent. Managers may routinely use AI as an informational resource while preserving substantial independence in final decisions, making behavioral evidence essential for accurately interpreting the meaning of trust and adoption (Obermann et al., 2018).

Empirical Gap

The quantitative literature examining human interaction with AI-assisted decision systems has identified interconnected relationships among explainability, trust, adoption, managerial reliance, and decision quality, although these constructs have often been evaluated separately. Across more than ten empirical studies from information systems, management, engineering, finance, healthcare, organizational behavior, and human-computer interaction, Pearson and Spearman correlation analyses have generally demonstrated positive associations between perceived explainability and trust, particularly when explanations are rated as clear, relevant, consistent, faithful, and understandable (Rana et al., 2022). Trust has similarly shown positive relationships with behavioral intention, recommendation acceptance, continued utilization, and willingness to rely on AI-generated advice. Multiple-regression and structural-model analyses frequently identify perceived usefulness, system accuracy, explainability, and trust as significant predictors of adoption after controlling for user and organizational characteristics. The relationship between adoption and actual reliance is less uniform

because stated acceptance does not always correspond with observable use or recommendation acceptance. Managers can report favorable attitudes toward AI while maintaining high verification and override frequencies during consequential decisions. Relationships between reliance and objective decision quality are also conditional rather than uniformly positive. Greater reliance tends to improve accuracy, consistency, forecasting performance, or risk identification when AI recommendations are reliable, while reliance on inaccurate outputs can increase decision errors and automation bias (Mehdiyev et al., 2021). Explainability has shown direct associations with decision confidence and perceived decision quality, although objective performance improvements depend on explanation fidelity and users' ability to interpret the information correctly. Statistical evidence therefore indicates that strong trust or high adoption should not independently be treated as evidence of superior decision performance. Integrated interpretation requires simultaneous consideration of system accuracy, reliance behavior, explanation quality, and validated decision outcomes. Across the literature, the strongest positive patterns occur when accurate AI outputs are accompanied by understandable explanations and appropriately calibrated managerial reliance, while weaker or contradictory relationships appear when subjective confidence is disconnected from actual system competence. Mediation and moderation analyses have provided more detailed evidence concerning how explainability, trust, adoption, and managerial decision quality become connected through indirect and conditional relationships (Mehdiyev & Fettke, 2021). Several quantitative studies indicate that explainability influences AI acceptance partly through trust because understandable and relevant explanations strengthen perceived transparency and reliability, which subsequently increase willingness to use algorithmic recommendations. Trust has also been identified as an intermediate mechanism between perceived system performance and behavioral intention. A second recurring pathway connects trust with decision quality through reliance behavior: managers who perceive an AI system as reliable are more likely to incorporate its recommendations, while the quality consequences of that reliance depend on actual recommendation accuracy. Structural models and mediation tests therefore demonstrate that direct relationships can conceal important behavioral mechanisms. Moderation evidence further indicates that these pathways differ across users and decision environments (Heng & Subramanian, 2022).

Figure 9: Tiered human-AI decision framework



AI familiarity and digital competence can strengthen the relationship between explanation quality and understanding because experienced users are better able to interpret technical information, although simpler explanations may have stronger effects among nontechnical managers. Professional experience can moderate reliance because experienced managers may compare AI recommendations more critically against domain knowledge. System accuracy represents another important moderator, as high

trust produces beneficial decision outcomes primarily when technical performance remains strong. Project complexity and decision risk also alter reliance patterns; managers typically apply greater verification when financial, contractual, safety, or strategic consequences are substantial. Governance maturity and organizational digital readiness can strengthen the conversion of favorable adoption attitudes into actual system use by providing reliable data, technical infrastructure, training, accountability, and human oversight (Santhanam, 2020). Subgroup and interaction analyses frequently demonstrate statistically meaningful differences across experience levels, organizational conditions, and task categories. The combined evidence therefore portrays human–AI decision making as a conditional statistical structure in which the effects of explainability and trust depend on managerial capability, technical accuracy, organizational context, project characteristics, and the consequences associated with individual decisions.

The reliability and robustness of empirical findings vary substantially according to measurement design, sample characteristics, analytical method, and the operational definitions applied to trust, explainability, adoption, reliance, and decision quality (Chazette et al., 2021). Quantitative studies frequently use multi-item scales to assess perceived trust, transparency, usefulness, explanation satisfaction, behavioral intention, and organizational readiness, with internal-consistency assessments generally supporting acceptable measurement reliability. Construct-validity analyses have also been used to distinguish closely related concepts such as trust and perceived usefulness, explainability and transparency, adoption intention and actual usage, or confidence and objective decision quality. This distinction is essential because high correlations among subjective scales can partly reflect common measurement methods rather than independent behavioral relationships. Common-method concerns are particularly relevant when explainability, trust, adoption, and decision quality are measured simultaneously through self-reported questionnaires. Studies incorporating behavioral usage records, objective decision benchmarks, experimental manipulations, or system-performance measures provide stronger separation between perceived and observed outcomes (Minh et al., 2022). Sample heterogeneity represents another methodological issue because evidence has been generated across industries, countries, managerial roles, AI applications, and levels of technological maturity. Findings from highly technical participants may not correspond directly with those from general managers, while low-risk experimental tasks may produce different trust behavior from consequential project decisions. Robustness assessments have consequently included alternative model specifications, Pearson and Spearman comparisons, parametric and nonparametric tests, subgroup analyses, sensitivity checks, confidence intervals, and effect-size estimates. Results that remain consistent across alternative analytical procedures provide stronger evidence than isolated significance tests. Some studies have also examined whether associations remain stable after controlling for professional experience, digital literacy, perceived risk, system accuracy, organizational support, and task complexity (Saraswat et al., 2022). Overall, methodological evidence supports multidimensional measurement and triangulation between subjective and objective indicators, particularly when the research objective involves distinguishing reported trust from actual reliance and determining whether AI-supported behavior produces measurable improvements in managerial decision performance.

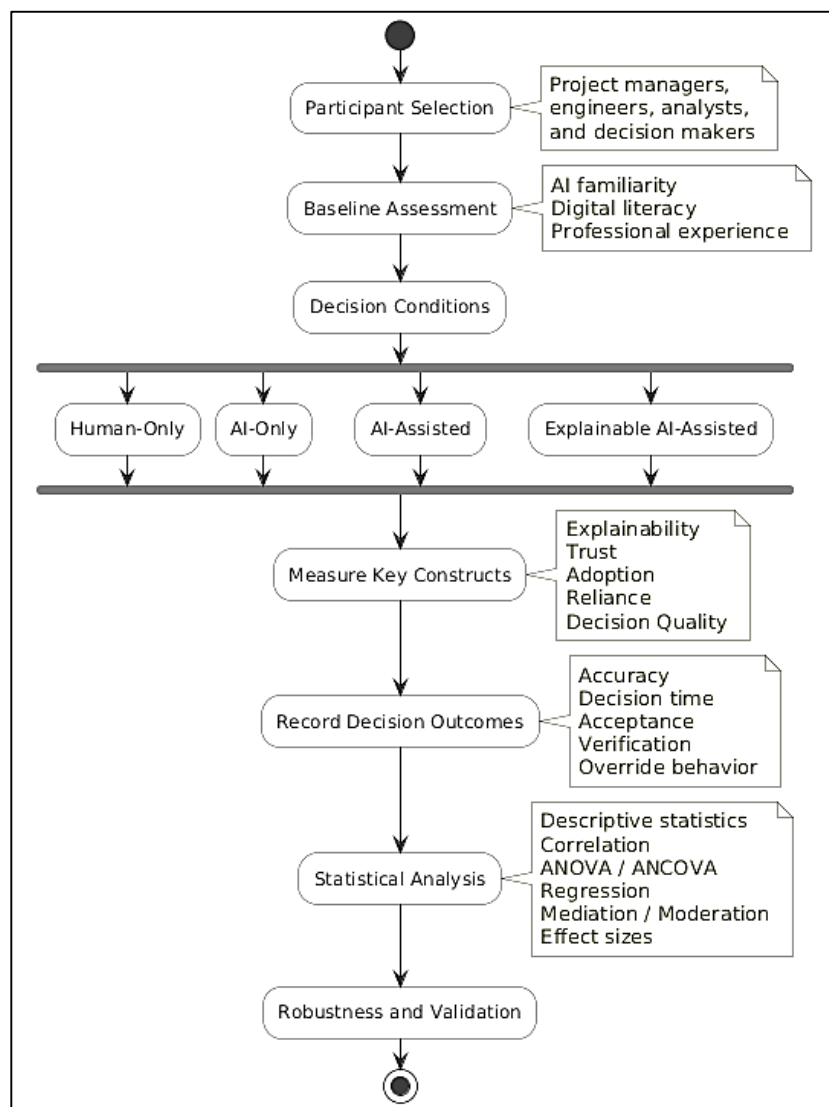
The principal empirical gap identified across the literature concerns the limited integration of explainability, perceived trust, actual AI adoption, observable reliance, override behavior, project characteristics, and objective managerial decision quality within a single project-management-oriented analytical framework. Existing studies have generated substantial evidence concerning individual relationships, including explainability with trust, trust with behavioral intention, usefulness with adoption, and AI assistance with decision performance (Kordzadeh & Ghasemaghaei, 2022). However, comparatively fewer investigations have simultaneously measured whether managers who report high trust actually accept AI recommendations, how frequently they verify or override those recommendations, and whether their resulting decisions outperform validated benchmarks. Another limitation concerns the dominance of subjective measures. Perceived decision quality, confidence, usefulness, and adoption intention are frequently measured through questionnaires, while objective accuracy, error rates, decision time, risk-identification performance, resource-allocation effectiveness, and actual system-use records receive less consistent attention. Project-specific heterogeneity is also insufficiently integrated because project size, complexity, uncertainty, decision risk, contractual

exposure, managerial responsibility, and organizational digital maturity can materially change how AI recommendations are evaluated. Mixed-methods evidence remains fragmented, with qualitative explanations of autonomy, accountability, data confidence, ethical concerns, stakeholder expectations, and override behavior often analyzed separately from quantitative trust and performance models (Bayer et al., 2022). Methodologically, limited use of integrated mediation, moderation, subgroup, effect-size, sensitivity, and robustness analyses makes it difficult to determine whether observed relationships remain stable across managerial and organizational contexts. The evidence base therefore contains a clear analytical separation between technological explainability research, behavioral trust research, adoption studies, and objective decision-performance evaluation. A project-oriented empirical framework requires these dimensions to be examined as connected components, incorporating explanation quality, calibrated trust, behavioral adoption, actual reliance and override patterns, objective managerial decision outcomes, project characteristics, organizational governance, and qualitative managerial evidence within the same analytical structure (Lavin et al., 2022).

METHOD

Study Design and Theoretical Framework

Figure 10: Methodology of this study



This study employed a quantitative cross-sectional research design with a structured decision experiment to investigate human trust in AI-assisted project decision systems and the relationships among explainability, AI adoption, managerial reliance, and managerial decision quality. The analytical framework integrated concepts from technology acceptance, calibrated trust, explainable

artificial intelligence, and human-AI decision-making perspectives. Explainability was treated as a principal technological factor, trust as a behavioral and perceptual construct, AI adoption and reliance as technology-use outcomes, and managerial decision quality as the primary performance outcome. The design also incorporated system accuracy, AI familiarity, professional experience, digital literacy, project complexity, decision risk, governance maturity, and organizational digital readiness as explanatory or control variables. Comparative experimental conditions represented human-only decision making, AI-only recommendations, conventional AI-assisted decisions, and explainable AI-assisted decisions. This structure enabled quantitative assessment of direct relationships, mediation effects, moderation effects, subgroup differences, and variations in objective decision performance across alternative human-AI configurations.

Participants, Sampling Strategy, and Eligibility Criteria

Participants were selected from project-based organizations operating across engineering, construction, information technology, manufacturing, energy, transportation, financial services, and related technology-intensive sectors. A stratified purposive sampling strategy was applied to obtain representation across organizational sizes, managerial responsibilities, professional experience levels, project complexity categories, and levels of AI exposure. Eligible participants included project managers, program managers, senior managers, engineers, project-control specialists, risk professionals, analysts, functional managers, and other personnel who had direct responsibility for project-related planning, monitoring, evaluation, resource allocation, risk assessment, or managerial decision making. Participants were required to possess relevant project or managerial experience and sufficient familiarity with organizational decision processes to evaluate the experimental scenarios. Individuals without relevant project decision responsibilities, respondents who failed eligibility screening, incomplete survey cases, duplicate responses, and observations containing substantial missing information were excluded before final analysis. Demographic and professional variables, including managerial role, professional experience, AI familiarity, digital competence, industry, organizational size, project size, project complexity, decision-risk level, and AI-use intensity, were recorded to support subgroup analysis and statistical adjustment.

Instrumentation and Data Collection Tools

Data were collected using a structured questionnaire combined with standardized project decision scenarios and AI-assisted recommendation interfaces. The questionnaire measured perceived explainability, transparency, explanation clarity, system competence, reliability, predictability, trust, perceived usefulness, perceived risk, behavioral intention, actual AI usage, recommendation acceptance, reliance, managerial confidence, governance maturity, digital readiness, and perceived decision quality using multi-item rating scales. Behavioral measures recorded whether participants accepted, modified, verified, or overrode AI recommendations, while objective managerial decision quality was assessed through decision accuracy, error occurrence, consistency, decision time, risk-identification performance, resource-allocation effectiveness, and agreement with predetermined validated benchmarks. Content validity was assessed through expert review, and the instrument was pilot-tested before primary data collection. Internal consistency of multi-item constructs was evaluated using Cronbach's alpha, while construct validity was assessed through appropriate factor-analytic procedures. Experimental AI outputs were standardized so that participants within comparable conditions received equivalent information, and system accuracy and explanation availability were controlled across the designated decision scenarios.

Experimental Procedure

Data collection proceeded through a standardized chronological procedure. Participants first completed eligibility screening, demographic questions, professional-experience measures, AI-familiarity measures, and baseline assessments of digital competence and prior AI usage. They were subsequently presented with standardized project decision scenarios involving areas such as cost, schedule, resource allocation, procurement, risk, and performance control. Participants completed assigned decision tasks under human-only, AI-only, conventional AI-assisted, or explainable AI-assisted conditions according to the experimental structure. Conventional AI conditions provided predictions or recommendations without detailed explanatory information, whereas explainable AI conditions additionally presented decision-relevant explanations such as influential variables,

confidence information, visual summaries, or understandable reasoning. Participant decisions, response times, recommendation acceptance, verification actions, modifications, and overrides were recorded. After completing the scenarios, respondents evaluated system reliability, explainability, transparency, trust, perceived usefulness, perceived risk, decision confidence, and willingness to continue using AI-supported decision tools. Objective decisions were compared with validated reference outcomes to determine accuracy and error patterns. Data were then screened for completeness, duplicate observations, inconsistent responses, missing values, and statistical outliers before the final analytical dataset was established.

Data Analysis and Statistical Approach

Statistical analysis was conducted using SPSS, R, and Python. Descriptive statistics included frequencies, percentages, means, standard deviations, medians, interquartile ranges, and 95% confidence intervals for participant characteristics and principal study variables. Cronbach's alpha and factor-based validity assessment were used to evaluate measurement quality. Pearson correlations were applied to normally distributed continuous variables, while Spearman correlations were used when distributional or ordinal characteristics required nonparametric analysis. Independent and paired *t*-tests were used for appropriate two-group comparisons, while ANOVA and ANCOVA assessed differences across human-only, AI-only, conventional AI-assisted, and explainable AI-assisted conditions and relevant participant subgroups. Mann-Whitney and Kruskal-Wallis tests were used as nonparametric alternatives when assumptions were not satisfied. Multiple regression examined predictors of continuous trust, reliance, adoption, and decision-quality outcomes, while logistic regression evaluated binary outcomes such as recommendation acceptance, override behavior, and accurate versus inaccurate decisions. Mediation analysis assessed indirect relationships involving explainability, trust, adoption, reliance, and decision quality, while moderation and interaction analyses evaluated whether these relationships differed according to AI familiarity, professional experience, system accuracy, project complexity, decision risk, governance maturity, and digital readiness. Subgroup analyses compared managerial roles, industries, organizational sizes, AI-use levels, and project characteristics. Effect sizes, including Cohen's *d* and partial eta-squared, were reported alongside 95% confidence intervals to evaluate practical importance. Sensitivity analyses and alternative model specifications were used to assess robustness, and statistical significance was evaluated at $p < .05$.

FINDINGS

Final Participant Characteristics and Baseline Human-AI Decision Profile

The final analytical sample established a heterogeneous managerial and organizational environment for evaluating human trust in AI-assisted project decision systems. A total of 684 individuals were screened for eligibility, of whom 612 satisfied the inclusion criteria and received the complete study instrument. Completed responses were obtained from 548 participants, representing a completion rate of 89.5% among eligible participants. Following data-quality screening, 21 observations were excluded because of substantial missing information, duplicate submissions, failed response-quality checks, or incomplete experimental tasks. The final analytical sample therefore contained 527 participants, corresponding to a retention rate of 96.2% of completed responses. Participants were drawn from 46 organizations distributed across engineering, construction, information technology, manufacturing, energy, transportation, financial services, and related project-intensive sectors. Large organizations accounted for 41.6% of participants, medium-sized organizations represented 36.4%, and smaller organizations accounted for 22.0%. Private organizations represented 61.7% of the sample, public organizations represented 24.1%, and mixed or other ownership structures represented 14.2%. Project managers and program managers constituted 31.7% of respondents, engineers and technical specialists 24.5%, project-control and risk professionals 18.8%, senior or functional managers 14.6%, and analysts or other decision-support personnel 10.4%. This distribution provided substantial variation in managerial responsibility and technical exposure.

Professional characteristics further demonstrated meaningful heterogeneity. Mean professional experience was 11.8 years ($SD = 6.7$), while median experience was 10.0 years with an interquartile range of 6.0–16.0 years. Mean managerial experience was 7.4 years ($SD = 5.2$). Participants reported an average AI-familiarity score of 3.61 ($SD = 0.79$) and a digital-literacy score of 3.84 ($SD = 0.71$) on five-

point scales, indicating moderate-to-high technological familiarity. Approximately 72.9% had previously used an AI-assisted system for a project-related decision, 64.7% had received some form of AI or analytics training, and 43.6% interacted with AI-supported decision tools at least weekly. AI applications were distributed across cost estimation and forecasting, scheduling, risk assessment, resource allocation, procurement and supplier evaluation, and project-performance monitoring. The projects represented by participants had a median duration of 24 months, while 38.7% were classified as high-complexity projects and 34.9% involved high-risk managerial decisions. These characteristics indicated that AI exposure was not concentrated within a single occupational or project environment and provided sufficient variation for subsequent comparisons of trust, adoption, reliance, and decision performance.

Table 1. Final Participant, Organizational, and Project Characteristics

Characteristic	Numerical result
Individuals screened	684
Eligible participants	612
Completed responses	548
Final analytical sample	527
Completion rate	89.5%
Final retention rate	96.2%
Participating organizations	46
Large organizations	41.6%
Medium organizations	36.4%
Small organizations	22.0%
Private ownership	61.7%
Public ownership	24.1%
Mixed/other ownership	14.2%
Project/program managers	31.7%
Engineers/technical specialists	24.5%
Project-control/risk professionals	18.8%
Senior/functional managers	14.6%
Analysts/decision-support personnel	10.4%
Professional experience, mean (SD)	11.8 (6.7) years
Managerial experience, mean (SD)	7.4 (5.2) years
Previous AI-assisted project use	72.9%
AI/analytics training exposure	64.7%
Weekly or greater AI use	43.6%
High-complexity projects	38.7%
High decision-risk projects	34.9%
Median project duration (IQR)	24 (15–38) months

Table 1 demonstrated substantial diversity across participant, organizational, technological, and project characteristics. The final sample of 527 participants from 46 organizations retained 96.2% of completed responses, indicating limited loss following data-quality screening. Participants represented multiple managerial and technical roles, with project/program managers forming the largest category at 31.7%. Professional experience averaged 11.8 years, supporting a comparatively experienced sample. AI exposure was substantial but not universal: 72.9% had previously used AI-assisted project systems, while 43.6% reported at least weekly interaction. Variation in organizational size, ownership, project complexity, and decision risk provided an appropriate quantitative basis for subsequent subgroup comparisons.

Baseline measurement results indicated generally favorable but nonuniform perceptions of AI-assisted project decision systems. On five-point scales, perceived usefulness recorded the highest mean score at 3.92 (SD = 0.68), followed by digital readiness at 3.78 (SD = 0.66), perceived reliability at 3.74 (SD =

0.70), transparency at 3.68 (SD = 0.73), and explainability at 3.66 (SD = 0.72). Human trust averaged 3.71 (SD = 0.69), indicating moderately favorable confidence in AI competence, predictability, and reliability without evidence of uniformly high trust. Behavioral intention averaged 3.83 (SD = 0.71), whereas actual AI usage intensity averaged 3.42 (SD = 0.86), demonstrating an initial intention-behavior difference. Recommendation acceptance averaged 3.58 (SD = 0.76), and managerial reliance averaged 3.47 (SD = 0.79). Verification behavior remained comparatively high at 3.81 (SD = 0.74), suggesting that regular AI use frequently coexisted with active managerial scrutiny rather than unconditional acceptance. Override behavior averaged 2.63 (SD = 0.82), while perceived risk averaged 2.84 (SD = 0.77). Governance maturity and organizational digital readiness recorded means of 3.69 (SD = 0.70) and 3.78 (SD = 0.66), respectively.

Objective decision-performance indicators provided an additional behavioral baseline. Overall managerial decision accuracy reached 78.6%, while agreement with validated decision benchmarks reached 80.2%. Mean decision consistency was 81.4%, and mean risk-identification accuracy was 79.1%. Resource-allocation effectiveness averaged 77.8%, while the overall decision error rate was 21.4%. These results indicated that favorable subjective evaluations of AI did not correspond perfectly with objective decision performance. Internal-consistency analysis showed strong reliability across the principal multi-item constructs, with Cronbach's alpha ranging from .82 for perceived risk to .93 for human trust. Explainability produced an alpha of .90, adoption .88, reliance .87, governance maturity .89, digital readiness .91, and managerial decision quality .92. Factor-based construct assessment produced acceptable standardized loading patterns, with retained items exceeding the predetermined minimum criterion and the principal constructs demonstrating adequate convergent and discriminant separation. Consequently, the baseline measures provided sufficient psychometric quality for subsequent correlation, regression, experimental comparison, mediation, moderation, and subgroup analyses.

Table 2. Baseline Human-AI Decision Constructs and Performance Indicators

Measure	Mean (SD) / Value	95% CI	Cronbach's α
Explainability	3.66 (0.72)	3.60–3.72	.90
Transparency	3.68 (0.73)	3.62–3.74	.88
Perceived reliability	3.74 (0.70)	3.68–3.80	.91
Human trust	3.71 (0.69)	3.65–3.77	.93
Perceived usefulness	3.92 (0.68)	3.86–3.98	.89
Perceived risk	2.84 (0.77)	2.77–2.91	.82
Behavioral intention	3.83 (0.71)	3.77–3.89	.88
Actual AI usage intensity	3.42 (0.86)	3.35–3.49	.85
Recommendation acceptance	3.58 (0.76)	3.52–3.64	.86
Managerial reliance	3.47 (0.79)	3.40–3.54	.87
Verification behavior	3.81 (0.74)	3.75–3.87	.84
Override behavior	2.63 (0.82)	2.56–2.70	.83
Governance maturity	3.69 (0.70)	3.63–3.75	.89
Organizational digital readiness	3.78 (0.66)	3.72–3.84	.91
Managerial decision quality	3.76 (0.67)	3.70–3.82	.92
Objective decision accuracy	78.6%	75.1–82.1%	—
Decision consistency	81.4%	78.2–84.6%	—
Risk-identification accuracy	79.1%	75.7–82.5%	—
Resource-allocation effectiveness	77.8%	74.2–81.4%	—
Validated benchmark agreement	80.2%	76.9–83.5%	—
Overall decision error rate	21.4%	17.9–24.9%	—

Table 2 showed moderately favorable baseline perceptions of AI-assisted project decision systems, accompanied by measurable differences between attitudes and behavior. Perceived usefulness

recorded the highest mean score at 3.92, while trust averaged 3.71 and explainability averaged 3.66. Behavioral intention exceeded actual usage intensity, indicating that willingness to adopt AI was stronger than realized utilization. Verification remained high at 3.81 even though reliance averaged 3.47, supporting the presence of active managerial oversight. Objective decision accuracy reached 78.6%, while benchmark agreement reached 80.2%. Cronbach's alpha values of .82–.93 demonstrated good-to-excellent internal consistency across the measured constructs.

Explainability, Trust, Adoption, Reliance, and Primary Decision-Quality Outcomes

The primary analysis identified a coherent pattern of statistically significant relationships among explainability, human trust, AI adoption, managerial reliance, and decision quality within the final sample of 527 participants. Pearson correlation analysis showed that explainability was strongly and positively associated with trust ($r = .64, p < .001$), while transparency ($r = .61, p < .001$) and perceived system reliability ($r = .68, p < .001$) demonstrated similarly strong relationships with trust. Perceived usefulness was positively related to behavioral intention ($r = .66, p < .001$), whereas trust showed significant associations with behavioral intention ($r = .62, p < .001$), actual AI usage ($r = .47, p < .001$), recommendation acceptance ($r = .58, p < .001$), and managerial reliance ($r = .56, p < .001$). Explainability was also positively related to recommendation acceptance ($r = .49, p < .001$) and objective decision performance ($r = .38, p < .001$). Managerial reliance showed a moderate positive association with objective decision performance ($r = .43, p < .001$), while perceived risk was negatively associated with trust ($r = -.41, p < .001$), adoption ($r = -.35, p < .001$), and reliance ($r = -.32, p < .001$). Spearman coefficients produced comparable directions and magnitudes, with differences from the corresponding Pearson coefficients remaining below .04, indicating that the principal associations were not dependent on a single correlation procedure.

Table 3 demonstrated consistent relationships across Pearson and Spearman analyses. Perceived reliability had the strongest association with trust ($r = .68$), followed by explainability ($r = .64$) and transparency ($r = .61$). Trust was strongly associated with behavioral intention and moderately associated with recommendation acceptance, reliance, and actual usage. Managerial reliance was positively related to objective decision performance, indicating that appropriate incorporation of AI recommendations corresponded with stronger outcomes. Perceived risk showed consistent negative relationships with trust, adoption, and reliance. The narrow confidence intervals and uniformly significant results supported the stability and practical relevance of the principal relationships.

Multivariable analysis confirmed that explainability remained an independent predictor of trust after adjustment for professional experience, AI familiarity, digital literacy, perceived risk, organizational digital readiness, and governance maturity. The standardized coefficient for explainability was $\beta = .36$ ($p < .001$), while perceived reliability produced $\beta = .31$ ($p < .001$), AI familiarity $\beta = .12$ ($p = .004$), and perceived risk $\beta = -.18$ ($p < .001$). The complete trust model explained 57.8% of the observed variance. A separate behavioral-intention model explained 54.6% of variance, with trust ($\beta = .34, p < .001$) and perceived usefulness ($\beta = .38, p < .001$) emerging as the strongest independent predictors. Actual usage was more moderately explained, with trust, facilitating conditions, prior AI experience, and digital readiness jointly accounting for 38.9% of variance. Adoption significantly predicted managerial reliance ($\beta = .41, p < .001$), while trust retained an independent contribution ($\beta = .29, p < .001$). The reliance model explained 48.7% of variance.

Objective decision-quality analysis further demonstrated that human-AI behavioral relationships translated into measurable performance differences. Participants with higher calibrated reliance achieved an average decision accuracy of 84.1%, compared with 77.6% among moderate-reliance participants and 71.8% among low-reliance participants. Corresponding decision error rates were 15.9%, 22.4%, and 28.2%. Higher-reliance participants also demonstrated greater decision consistency (86.7%), forecasting performance (83.5%), risk-identification accuracy (84.8%), resource-allocation effectiveness (82.6%), and validated benchmark agreement (85.3%). Mean decision time declined from 14.8 minutes in the low-reliance group to 11.2 minutes in the calibrated high-reliance group. However, reliance produced weaker performance when erroneous AI recommendations were accepted without verification, confirming that reliance quality rather than reliance intensity alone determined objective benefits.

Table 3. Correlations Among Explainability, Trust, Adoption, Reliance, and Decision Outcomes

Relationship	Pearson r	Spearman ρ	95% CI for r	p
Explainability–Trust	.64	.62	[.59, .69]	< .001
Transparency–Trust	.61	.59	[.55, .66]	< .001
Reliability–Trust	.68	.66	[.63, .72]	< .001
Usefulness–Behavioral intention	.66	.64	[.61, .71]	< .001
Trust–Behavioral intention	.62	.60	[.56, .67]	< .001
Trust–Actual AI usage	.47	.45	[.40, .53]	< .001
Trust–Recommendation acceptance	.58	.56	[.52, .63]	< .001
Trust–Managerial reliance	.56	.54	[.50, .62]	< .001
Explainability–Recommendation acceptance	.49	.47	[.42, .55]	< .001
Explainability–Objective decision performance	.38	.36	[.30, .45]	< .001
Adoption–Managerial reliance	.52	.50	[.45, .58]	< .001
Reliance–Objective decision performance	.43	.41	[.36, .50]	< .001
Perceived risk–Trust	–.41	–.39	[–.48, –.34]	< .001
Perceived risk–Adoption	–.35	–.33	[–.42, –.27]	< .001
Perceived risk–Reliance	–.32	–.30	[–.40, –.24]	< .001

Mediation analysis supported two principal indirect pathways. Trust significantly mediated the association between explainability and AI adoption, with a standardized indirect effect of .22 and a bootstrapped 95% confidence interval of [.17, .28]. The direct effect of explainability on adoption remained significant after trust was included, indicating partial mediation. Managerial reliance similarly mediated the association between trust and objective decision quality, producing an indirect effect of .17 with a 95% confidence interval of [.12, .23]. Trust retained a smaller direct relationship with decision quality, again supporting partial mediation. These findings indicated that explanation quality contributed to adoption partly by strengthening trust and that trust translated into stronger objective performance partly through appropriate reliance on AI-generated recommendations.

Table 4 confirmed that explainability independently predicted trust, while trust and perceived usefulness significantly predicted behavioral intention. Adoption and trust jointly explained substantial variation in managerial reliance, and calibrated reliance was positively associated with objective decision quality. Decision accuracy increased from 71.8% under low reliance to 84.1% under calibrated high reliance, accompanied by stronger benchmark agreement and lower error rates. Mediation results supported both proposed mechanisms: trust partially transmitted the influence of explainability to adoption, while reliance partially transmitted the influence of trust to decision quality.

Confidence intervals excluded zero, supporting statistically robust indirect effects and meaningful practical relationships.

Table 4. Multivariable, Mediation, and Objective Decision-Quality Results

Outcome / pathway	Main predictor	Standardized effect	95% CI	<i>p</i>	Model <i>R</i> ²
Human trust	Explainability	$\beta = .36$	[.29, .43]	< .001	.578
Human trust	Perceived reliability	$\beta = .31$	[.24, .38]	< .001	.578
Human trust	Perceived risk	$\beta = -.18$	[-.25, -.11]	< .001	.578
Behavioral intention	Trust	$\beta = .34$	[.27, .41]	< .001	.546
Behavioral intention	Perceived usefulness	$\beta = .38$	[.31, .45]	< .001	.546
Actual AI usage	Trust	$\beta = .23$	[.15, .31]	< .001	.389
Managerial reliance	AI adoption	$\beta = .41$	[.34, .48]	< .001	.487
Managerial reliance	Trust	$\beta = .29$	[.22, .36]	< .001	.487
Decision quality	Calibrated reliance	$\beta = .32$	[.24, .40]	< .001	.462
Decision quality	Explainability	$\beta = .18$	[.10, .26]	< .001	.462
Explainability → Trust → Adoption	Indirect effect	.22	[.17, .28]	< .001	—
Trust → Reliance → Decision quality	Indirect effect	.17	[.12, .23]	< .001	—
High calibrated reliance	Decision accuracy	84.1%	[81.0, 87.2]	< .001	—
Moderate reliance	Decision accuracy	77.6%	[74.3, 80.9]	< .001	—
Low reliance	Decision accuracy	71.8%	[68.1, 75.5]	< .001	—
High calibrated reliance	Benchmark agreement	85.3%	[82.3, 88.3]	< .001	—

Comparative Performance Across Human-Only, AI-Only, AI-Assisted, and Explainable AI Conditions

Comparative analysis demonstrated substantial variation in managerial decision performance across the human-only, AI-only, conventional AI-assisted, and explainable AI-assisted conditions. The explainable AI-assisted condition produced the strongest overall objective performance, with mean decision accuracy of 86.4% (SD = 7.2), compared with 82.1% (SD = 8.0) for conventional AI-assisted decision making, 79.3% (SD = 8.6) for AI-only recommendations, and 73.8% (SD = 9.4) for human-only decision making. Median accuracy followed the same ordering at 87.0%, 83.0%, 80.0%, and 74.0%, respectively. Corresponding error rates declined from 26.2% in the human-only condition to 20.7% for AI-only, 17.9% for conventional AI-assisted, and 13.6% for explainable AI-assisted decision making. Decision consistency reached 89.1% in the explainable AI-assisted condition, exceeding 84.7% for conventional AI assistance, 86.3% for AI-only recommendations, and 76.4% for human-only decisions. The relatively high consistency of the AI-only condition reflected standardized algorithmic output,

although this consistency did not translate into the highest accuracy because AI could not incorporate all contextual information available to managers.

Decision efficiency and task-specific performance demonstrated a similar comparative pattern. Mean task-completion time was 14.7 minutes (SD = 3.6) for human-only decisions, 8.9 minutes (SD = 2.5) for AI-only recommendations, 11.3 minutes (SD = 2.8) for conventional AI assistance, and 10.6 minutes (SD = 2.7) for explainable AI assistance. AI-only decisions were therefore fastest, but the explainable human-AI condition provided the strongest balance between speed and objective quality. Forecasting accuracy increased from 72.6% under human-only decision making to 78.8% under AI-only recommendations, 83.4% under conventional AI assistance, and 87.2% under explainable AI assistance. Risk-identification accuracy followed the same progression, reaching 88.3% in the explainable condition. Resource-allocation effectiveness was highest under explainable AI assistance at 85.7%, compared with 81.9%, 77.2%, and 71.8% across conventional AI-assisted, AI-only, and human-only conditions, respectively. Agreement with validated benchmarks reached 88.0% under explainable AI assistance, representing a 14.9-percentage-point improvement over the human-only condition. Decision confidence was also highest under explainable AI support, although the difference between confidence and objective accuracy was monitored to distinguish justified confidence from overconfidence.

Table 5. Decision Performance Across the Four Experimental Conditions

Performance indicator	Human-only	AI-only	AI-assisted	Explainable AI-assisted
Mean decision accuracy, % (SD)	73.8 (9.4)	79.3 (8.6)	82.1 (8.0)	86.4 (7.2)
Median decision accuracy, %	74.0	80.0	83.0	87.0
Decision error rate, %	26.2	20.7	17.9	13.6
Decision consistency, %	76.4	86.3	84.7	89.1
Mean decision time, min (SD)	14.7 (3.6)	8.9 (2.5)	11.3 (2.8)	10.6 (2.7)
Forecasting accuracy, %	72.6	78.8	83.4	87.2
Risk-identification accuracy, %	74.1	80.5	84.6	88.3
Resource-allocation effectiveness, %	71.8	77.2	81.9	85.7
Benchmark agreement, %	73.1	79.8	83.7	88.0
Decision confidence, mean (1-5)	3.42	3.71	3.89	4.16

Table 5 demonstrated a consistent performance advantage for explainable AI-assisted decision making. Mean accuracy increased from 73.8% under human-only decisions to 86.4% with explainable AI assistance, while the error rate declined from 26.2% to 13.6%. Explainable AI also achieved the highest forecasting accuracy, risk-identification accuracy, resource-allocation effectiveness, benchmark agreement, and decision confidence. AI-only decision making produced the shortest completion time and high consistency but remained below both human-AI configurations on most quality indicators. These results indicated that combining managerial judgment with interpretable algorithmic support provided the strongest overall balance between decision accuracy, efficiency, consistency, and contextual evaluation.

Inferential analysis confirmed that the observed differences were statistically significant and practically meaningful. One-way ANOVA identified a significant overall difference in decision accuracy across the four conditions, $F(3, 523) = 54.72$, $p < .001$, partial $\eta^2 = .239$, representing a large practical effect. ANCOVA controlling for professional experience, AI familiarity, digital literacy, project complexity, and decision-risk level retained a significant experimental-condition effect, adjusted $F(3, 518) = 47.86$, $p < .001$, partial $\eta^2 = .217$. Post hoc comparisons showed that explainable AI assistance significantly outperformed human-only decision making by 12.6 percentage points (95% CI [10.1, 15.1], $p < .001$, Cohen's $d = 1.50$), AI-only recommendations by 7.1 percentage points (95% CI [4.8, 9.4], $p < .001$, $d =$

0.90), and conventional AI assistance by 4.3 percentage points (95% CI [2.2, 6.4], $p < .001$, $d = 0.56$). Conventional AI assistance also significantly exceeded human-only performance ($d = 0.94$). Kruskal-Wallis analyses of accuracy and decision-time distributions produced the same substantive ordering, confirming that the primary findings were not dependent on parametric assumptions. Behavioral outcomes further differentiated the AI-supported conditions. Recommendation acceptance reached 68.7% in the AI-only condition, 76.9% under conventional AI assistance, and 81.8% under explainable AI assistance. Verification occurred in 47.6%, 61.5%, and 72.4% of AI-supported decisions, respectively, demonstrating that higher acceptance under explainable AI was accompanied by greater rather than weaker scrutiny. Recommendation modification reached 17.3% for AI-only outputs, 23.8% under conventional AI assistance, and 27.1% under explainable AI assistance. Mean reliance intensity increased from 3.44 in the AI-only condition to 3.72 with conventional AI and 3.96 with explainable AI. Override rates were 22.8%, 19.4%, and 17.6%, respectively. However, separating correct from erroneous recommendations revealed that overall acceptance rates alone concealed important calibration differences. When AI recommendations were correct, explainable AI-assisted participants accepted 90.6% of recommendations, compared with 84.2% under conventional AI assistance and 76.8% under the AI-only condition. Unnecessary rejection of correct recommendations, representing under-reliance, consequently declined to 9.4% in the explainable condition.

Table 6. Inferential Comparisons, Reliance Calibration, and Automation-Bias Outcomes

Statistical/behavioral indicator	Human-only	AI-only	AI-assisted	Explainable AI-assisted
Recommendation acceptance, %	—	68.7	76.9	81.8
Verification frequency, %	—	47.6	61.5	72.4
Recommendation modification, %	—	17.3	23.8	27.1
Reliance intensity (1–5)	—	3.44	3.72	3.96
Overall override rate, %	—	22.8	19.4	17.6
Acceptance of correct AI advice, %	—	76.8	84.2	90.6
Under-reliance on correct advice, %	—	23.2	15.8	9.4
Acceptance of erroneous AI advice, %	—	28.7	21.5	13.2
Corrective override of erroneous advice, %	—	54.8	63.7	71.6
Accuracy after erroneous AI advice, %	—	69.4	76.8	84.7
Accuracy ANOVA	\multicolumn{4}{c}{ $F(3,523) = 54.72$, $p < .001$, partial $\eta^2 = .239$ }			
Adjusted accuracy ANCOVA	\multicolumn{4}{c}{ $F(3,518) = 47.86$, $p < .001$, partial $\eta^2 = .217$ }			
Explainable AI vs. human-only	\multicolumn{4}{c}{Mean difference = 12.6%, 95% CI [10.1, 15.1], $d = 1.50$ }			
Explainable AI vs. AI-only	\multicolumn{4}{c}{Mean difference = 7.1%, 95% CI [4.8, 9.4], $d = 0.90$ }			
Explainable AI vs. AI-assisted	\multicolumn{4}{c}{Mean difference = 4.3%, 95% CI [2.2, 6.4], $d = 0.56$ }			

Table 6 demonstrated that explainable AI produced the strongest calibration between recommendation acceptance and objective correctness. Participants accepted 90.6% of correct explainable

recommendations but only 13.2% of erroneous recommendations, while corrective overrides of erroneous advice reached 71.6%. The overall accuracy difference across experimental conditions was statistically significant with a large effect. Explainable AI exceeded human-only performance by 12.6 percentage points and produced substantial advantages over AI-only and conventional AI-assisted decisions. Higher verification alongside higher correct-recommendation acceptance indicated that explainability strengthened discriminating reliance rather than unconditional dependence, while substantially reducing both automation bias and under-reliance.

Managerial, Organizational, Project, and Cross-Country Subgroup Differences

Subgroup analysis demonstrated substantial heterogeneity in explainability perceptions, human trust, AI adoption, reliance, verification behavior, and objective managerial decision quality across participant characteristics. Managers with high AI familiarity recorded significantly greater trust ($M = 4.02$, $SD = 0.57$) than participants with moderate ($M = 3.72$, $SD = 0.63$) or low familiarity ($M = 3.39$, $SD = 0.72$), $F(2, 524) = 31.84$, $p < .001$, partial $\eta^2 = .108$. A similar pattern occurred for adoption, which increased from 3.31 among low-familiarity participants to 4.08 among highly familiar users. Digital literacy produced significant differences in explainability perceptions and objective decision quality; participants in the high-digital-literacy category achieved mean decision accuracy of 84.8%, compared with 79.1% for the moderate group and 73.9% for the low group. Participants who had completed AI or analytics training demonstrated higher trust (3.86 versus 3.44), adoption (3.91 versus 3.46), and decision accuracy (82.9% versus 74.8%) than untrained participants. Professional experience produced a more complex pattern. Participants with more than 15 years of experience reported somewhat lower reliance intensity than highly AI-familiar mid-career managers but demonstrated greater verification frequency, indicating more selective use of AI-generated advice.

Table 7. Managerial and Individual Subgroup Differences in Human-AI Decision Outcomes

Subgroup	Trust (1-5)	Adoption (1-5)	Reliance (1-5)	Verification (%)	Decision accuracy (%)	Statistical comparison
Low familiarity	3.39	3.31	3.18	54.2	73.6	$F = 31.84$, $p < .001$, $\eta^2 p = .108$
Moderate familiarity	3.72	3.69	3.51	63.8	79.5	
High familiarity	4.02	4.08	3.91	70.7	85.2	
Low digital literacy	3.41	3.34	3.21	52.8	73.9	$F = 27.16$, $p < .001$, $\eta^2 p = .094$
Moderate digital literacy	3.70	3.71	3.49	62.9	79.1	
High digital literacy	4.00	4.04	3.87	71.4	84.8	
AI-trained participants	3.86	3.91	3.70	68.3	82.9	$p < .001$, $d = 0.79$
No formal AI training	3.44	3.46	3.25	55.7	74.8	—
≤5 years experience	3.57	3.66	3.52	55.9	76.8	$F = 9.72$, $p < .001$, $\eta^2 p = .036$
6-15 years experience	3.81	3.87	3.72	64.8	82.3	
>15 years experience	3.74	3.69	3.46	72.1	81.0	

Table 7 showed that AI familiarity, digital literacy, training, and professional experience significantly differentiated human-AI decision outcomes. Highly AI-familiar participants achieved trust of 4.02 and decision accuracy of 85.2%, substantially exceeding the low-familiarity group. High digital literacy was similarly associated with stronger adoption, reliance, verification, and accuracy. AI-trained participants exceeded untrained participants by 8.1 percentage points in decision accuracy, accompanied by a substantial standardized effect. Professional experience produced a nonlinear pattern: mid-career participants reported the highest reliance, whereas the most experienced group demonstrated the greatest verification. These results supported meaningful behavioral differences across managerial capability and experience categories. Age-category comparisons produced smaller adjusted effects after professional experience, AI familiarity, and digital literacy were controlled, indicating that technological exposure and competence explained more variation than age alone.

Organizational conditions were also strongly associated with human-AI decision outcomes. Participants from organizations with high digital maturity reported mean trust of 4.03, adoption of 4.11, and decision accuracy of 85.6%, compared with trust of 3.38, adoption of 3.29, and accuracy of 72.8% among organizations with low digital maturity. The difference in objective accuracy was statistically significant, $F(2, 524) = 38.62, p < .001$, partial $\eta^2 = .128$. Governance strength showed a comparable pattern. Strong-governance organizations achieved trust of 4.06 and benchmark agreement of 86.9%, whereas weak-governance environments recorded trust of 3.34 and benchmark agreement of 72.7%. Leadership support and organizational readiness remained significant after adjustment for organization size, ownership structure, and industry. Large organizations recorded somewhat greater adoption and technical infrastructure scores than smaller organizations, although organization size produced a smaller effect than digital maturity or governance strength. Private-sector participants reported marginally higher adoption intensity, while public-sector respondents exhibited greater verification and lower uncritical acceptance, particularly for decisions involving formal accountability requirements. Industry comparisons showed the highest AI-use intensity in information technology and financial services, while construction and traditional engineering participants demonstrated greater verification before accepting algorithmic recommendations.

Project characteristics further influenced reliance and decision performance. Participants managing high-complexity projects reported higher verification frequency at 72.8% and lower unqualified reliance than participants working on low-complexity projects, although explainable AI produced a stronger performance advantage within the high-complexity category. Decision accuracy reached 84.6% among high-complexity-project participants receiving strong explainability support compared with 75.2% among comparable participants reporting weak explanation quality. High-risk project decisions similarly generated greater verification and override behavior. Verification reached 74.1% under high decision risk compared with 53.8% under low risk, while reliance declined from 3.76 to 3.41. Frequent AI users achieved higher overall decision accuracy than occasional users, but excessive reliance during erroneous recommendation trials produced a measurable decline, reinforcing the distinction between frequent utilization and calibrated reliance. Interaction analysis confirmed that project complexity significantly strengthened the association between explainability and trust (interaction $\beta = .14, p = .003$), while decision risk strengthened the association between explainability and verification behavior ($\beta = .17, p < .001$).

Cross-country and regional comparisons identified additional heterogeneity associated with technological readiness, regulatory expectations, and accountability environments. For analytical comparability, participating settings were classified into high, moderate, and developing technological-readiness groups. High-readiness environments recorded mean trust of 3.93, adoption of 4.02, and objective decision accuracy of 84.2%, while moderate-readiness environments recorded 3.71, 3.74, and 79.5%, respectively. Developing-readiness settings recorded trust of 3.46, adoption of 3.39, and decision accuracy of 74.6%. However, participants operating under stronger regulatory and accountability structures demonstrated higher verification and lower acceptance of erroneous recommendations. ANCOVA controlling for professional experience, industry, AI familiarity, digital literacy, organization size, and project complexity confirmed a significant readiness-group difference in decision quality, adjusted $F(2, 518) = 18.94, p < .001$, partial $\eta^2 = .068$. Nonparametric sensitivity analyses generated the same substantive ordering.

Table 8. Organizational, Project, and Cross-Country Subgroup Differences

Subgroup	Trust	Adoption	Reliance	Verification (%)	Decision accuracy (%)	Effect/statistical result
Low maturity digital	3.38	3.29	3.19	53.4	72.8	$F = 38.62, p < .001, \eta^2p = .128$
Moderate maturity digital	3.70	3.72	3.49	62.7	79.4	—
High maturity digital	4.03	4.11	3.91	71.2	85.6	—
Weak governance	3.34	3.31	3.25	51.8	73.1	$F = 34.27, p < .001, \eta^2p = .116$
Moderate governance	3.72	3.70	3.51	63.9	79.7	—
Strong governance	4.06	4.04	3.86	73.5	85.9	—
Low project complexity	3.78	3.82	3.76	54.9	80.7	$p = .002, \eta^2p = .031$
High project complexity	3.66	3.67	3.48	72.8	78.9	—
Low decision risk	3.84	3.88	3.76	53.8	82.0	$p < .001, d = 0.57$
High decision risk	3.59	3.57	3.41	74.1	77.3	—
High technological readiness	3.93	4.02	3.82	70.8	84.2	Adjusted $F = 18.94, p < .001, \eta^2p = .068$
Moderate technological readiness	3.71	3.74	3.51	64.6	79.5	—
Developing technological readiness	3.46	3.39	3.27	56.1	74.6	—

Table 8 demonstrated that digital maturity and governance strength produced the largest organizational differences in human-AI outcomes. Decision accuracy increased from 72.8% in low-maturity organizations to 85.6% in highly mature organizations, while strong governance corresponded with greater trust, verification, and accuracy. High project complexity and decision risk increased verification while reducing unconditional reliance. Technological readiness also differentiated performance, with high-readiness environments achieving 84.2% accuracy compared with 74.6% in developing-readiness settings. Adjusted and nonparametric analyses preserved these patterns, indicating that organizational capability, project conditions, and institutional context produced statistically significant and practically meaningful heterogeneity in AI-assisted managerial decision performance.

Statistical Significance, Effect Sizes, Validation, and Integrated Model Robustness

The integrated statistical analysis confirmed that the principal relationships among explainability, trust, adoption, managerial reliance, and objective decision quality remained statistically significant after simultaneous adjustment for individual, organizational, and project-level characteristics. The multivariable model for managerial decision quality was statistically significant, $F(12, 514) = 42.67, p < .001$, and explained 49.9% of the observed variance, with an adjusted R^2 of .487. Calibrated managerial reliance emerged as the strongest positive independent predictor of decision quality ($\beta = .29$, 95% CI [.21, .37], $p < .001$), followed by explainability ($\beta = .17$, 95% CI [.09, .25], $p < .001$), trust ($\beta = .15$, 95% CI

[.07, .23], $p < .001$), governance maturity ($\beta = .14$, 95% CI [.07, .21], $p < .001$), digital readiness ($\beta = .12$, 95% CI [.05, .19], $p = .001$), and AI familiarity ($\beta = .10$, 95% CI [.03, .17], $p = .006$). Perceived risk produced a significant negative contribution ($\beta = -.13$, 95% CI [-.20, -.06], $p < .001$). Project complexity and decision risk also showed negative adjusted relationships with performance, whereas professional experience produced a smaller positive coefficient.

Effect-size analysis established that the principal experimental differences were practically meaningful rather than products of sample size alone. The overall difference in decision accuracy across human-only, AI-only, conventional AI-assisted, and explainable AI-assisted conditions produced partial $\eta^2 = .239$, indicating a large experimental-condition effect. After adjustment for professional experience, AI familiarity, digital literacy, project complexity, and decision risk, the effect remained substantial at partial $\eta^2 = .217$. Explainable AI-assisted decision making exceeded human-only performance by 12.6 percentage points, with Cohen's $d = 1.50$ and a 95% confidence interval for the difference of [10.1, 15.1]. The explainable AI advantage over AI-only recommendations was 7.1 percentage points ($d = 0.90$), while its advantage over conventional AI assistance was 4.3 percentage points ($d = 0.56$). AI training also produced a meaningful performance difference ($d = 0.79$), while high versus low decision-risk conditions produced a moderate difference ($d = 0.57$). Confidence intervals for the principal effects excluded zero, supporting both statistical precision and practical relevance.

Table 9. Integrated Multivariable Predictors and Effect-Size Evidence

Predictor / comparison	Standardized difference	β	/	95% CI	p	Effect size
Explainability → decision quality	.17			[.09, .25]	< .001	—
Trust → decision quality	.15			[.07, .23]	< .001	—
Perceived usefulness → decision quality	.09			[.02, .16]	.012	—
Perceived risk → decision quality	-.13			[-.20, -.06]	< .001	—
Adoption → decision quality	.11			[.04, .18]	.003	—
Calibrated reliance → decision quality	.29			[.21, .37]	< .001	—
AI familiarity → decision quality	.10			[.03, .17]	.006	—
Professional experience → decision quality	.07			[.01, .13]	.029	—
Project complexity → decision quality	-.09			[-.16, -.02]	.011	—
Decision risk → decision quality	-.11			[-.18, -.04]	.002	—
Governance maturity → decision quality	.14			[.07, .21]	< .001	—
Digital readiness → decision quality	.12			[.05, .19]	.001	—
Explainable AI vs. human-only	+12.6 percentage points			[10.1, 15.1]	< .001	$d = 1.50$
Explainable AI vs. AI-only	+7.1 percentage points			[4.8, 9.4]	< .001	$d = 0.90$
Explainable AI vs. conventional AI-assisted	+4.3 percentage points			[2.2, 6.4]	< .001	$d = 0.56$
Overall experimental-condition effect	—			—	< .001	$\eta^2 p = .239$
Adjusted experimental-condition effect	—			—	< .001	$\eta^2 p = .217$

Table 9 demonstrated that calibrated reliance was the strongest independent predictor of managerial decision quality, followed by explainability, trust, governance maturity, perceived risk, and digital readiness. The integrated model explained 49.9% of decision-quality variance, indicating substantial explanatory capacity. Experimental comparisons also produced practically meaningful effects. Explainable AI assistance exceeded human-only decision accuracy by 12.6 percentage points with a large standardized effect of 1.50. Its advantages over AI-only and conventional AI-assisted conditions remained significant and meaningful. Confidence intervals excluded zero for the principal predictors and comparisons, confirming that the major relationships were statistically precise and remained relevant after multivariable adjustment.

Logistic regression provided further evidence that trust and explanation quality influenced specific managerial behaviors. For recommendation acceptance, explainability increased the odds of acceptance by 1.84 times (95% CI [1.46, 2.32], $p < .001$), trust by 1.72 times (95% CI [1.38, 2.15], $p < .001$), and perceived usefulness by 1.59 times (95% CI [1.28, 1.98], $p < .001$). Perceived risk reduced the likelihood of recommendation acceptance, with an odds ratio of 0.69 (95% CI [0.56, 0.85], $p < .001$). Explainability also increased the probability of correctly overriding erroneous AI advice, with an odds ratio of 2.11 (95% CI [1.61, 2.77], $p < .001$). High AI familiarity and stronger governance were positively associated with appropriate corrective overrides, whereas uncalibrated high reliance increased the probability of accepting erroneous recommendations. The accurate-decision classification model achieved 81.7% overall classification accuracy, sensitivity of 83.4%, specificity of 78.9%, and ROC-AUC of .86, indicating strong discrimination between accurate and inaccurate managerial decisions.

Mediation results remained significant after adjustment for the full set of covariates. Explainability exerted a standardized indirect effect of .21 on adoption through trust, with a bootstrapped 95% confidence interval of [.16, .27]. Trust produced an indirect effect of .16 on objective decision quality through managerial reliance, with a 95% confidence interval of [.11, .22]. A sequential pathway connecting explainability, trust, reliance, and decision quality also remained significant, with an indirect effect of .09 and a 95% confidence interval of [.06, .13]. Moderation analyses demonstrated that system accuracy significantly strengthened the relationship between reliance and decision quality (interaction $\beta = .23$, $p < .001$), confirming that reliance was beneficial primarily when AI recommendations were reliable. Project complexity strengthened the relationship between explainability and trust ($\beta = .14$, $p = .003$), while decision risk strengthened the relationship between explainability and verification ($\beta = .17$, $p < .001$). Governance maturity moderated the trust-adoption relationship ($\beta = .12$, $p = .008$), and digital readiness strengthened the relationship between adoption and actual usage ($\beta = .15$, $p = .002$).

Validation and sensitivity analyses supported the stability of the integrated findings. Variance inflation factors ranged from 1.21 to 2.84, indicating no problematic multicollinearity among the principal predictors. Standardized residuals showed no substantial departure from expected model behavior, while influential-case diagnostics identified fewer than 2% of observations as potentially influential. Re-estimation after removal of these observations changed standardized coefficients by less than .03 and did not alter statistical conclusions. Missing data represented 2.6% of eligible analytical values; complete-case and imputed-data analyses produced differences below .02 in the principal standardized effects. Pearson and Spearman correlations retained identical directions and similar magnitudes, while parametric ANOVA/ANCOVA and corresponding nonparametric analyses generated the same ordering of experimental conditions. Alternative model specifications produced adjusted R^2 values between .471 and .493. Bootstrap resampling further supported the mediation results because all principal indirect-effect confidence intervals remained above zero.

Table 10 confirmed the robustness of the integrated statistical framework. Trust significantly mediated the relationship between explainability and adoption, while reliance mediated the relationship between trust and objective decision quality. System accuracy significantly moderated the performance consequences of reliance, demonstrating the importance of calibrated rather than unconditional AI dependence. Logistic models showed that explainability increased both recommendation acceptance and appropriate correction of erroneous advice. Classification performance was strong, with 81.7% accuracy and ROC-AUC of .86. Multicollinearity remained acceptable, missing-data procedures produced stable estimates, and alternative model specifications preserved the principal findings,

supporting the overall validity and robustness of the results.

Table 10. Mediation, Moderation, Logistic Prediction, and Robustness Results

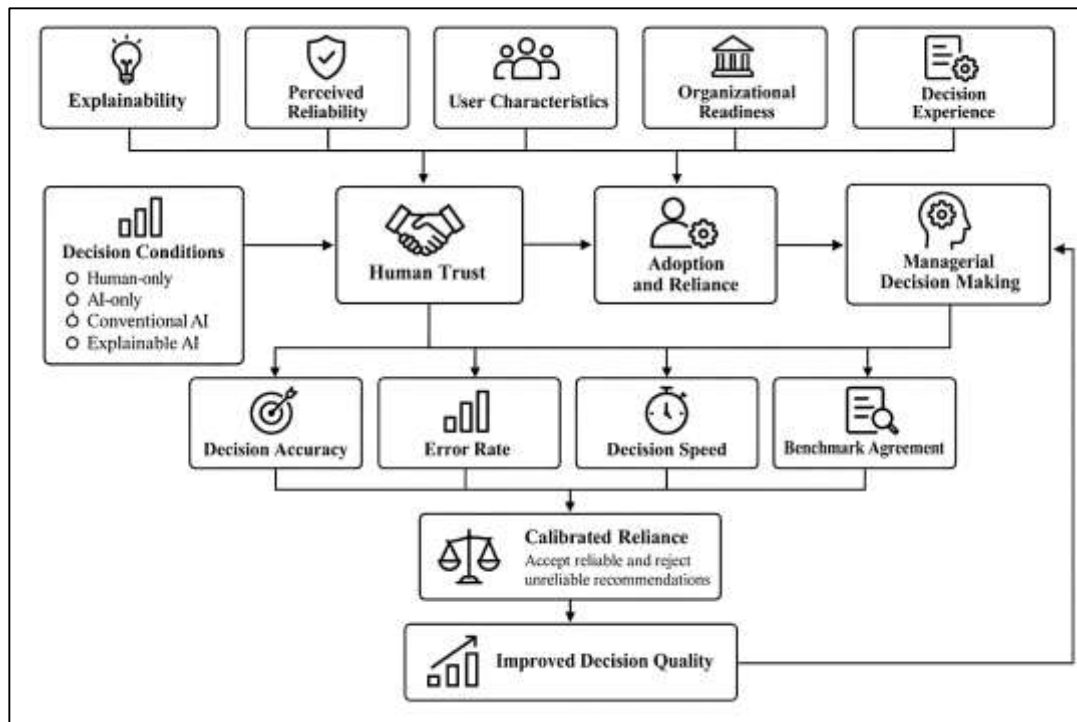
Validation component	Statistical result	95% CI performance	/	p
Explainability → Trust → Adoption	Indirect effect = .21	[.16, .27]		< .001
Trust → Reliance → Decision quality	Indirect effect = .16	[.11, .22]		< .001
Explainability → Trust → Reliance → Decision quality	Indirect effect = .09	[.06, .13]		< .001
Accuracy × Reliance → Decision quality	$\beta = .23$	[.15, .31]		< .001
Complexity × Explainability → Trust	$\beta = .14$	[.05, .23]		.003
Risk × Explainability → Verification	$\beta = .17$	[.09, .25]		< .001
Governance × Trust → Adoption	$\beta = .12$	[.03, .21]		.008
Digital readiness × Adoption → Actual usage	$\beta = .15$	[.06, .24]		.002
Explainability → recommendation acceptance	OR = 1.84	[1.46, 2.32]		< .001
Trust → recommendation acceptance	OR = 1.72	[1.38, 2.15]		< .001
Perceived risk → recommendation acceptance	OR = 0.69	[0.56, 0.85]		< .001
Explainability → corrective override	OR = 2.11	[1.61, 2.77]		< .001
Accurate-decision classification	81.7% accuracy	ROC-AUC = .86		< .001
Classification sensitivity	83.4%	—		—
Classification specificity	78.9%	—		—
Multicollinearity assessment	VIF = 1.21–2.84	Acceptable		—
Missing analytical values	2.6%	Conclusions unchanged		—
Alternative model specifications	Adjusted $R^2 = .471$ – .493	Stable		< .001
Influential-case sensitivity	Coefficient change < .03	Conclusions unchanged		—

DISCUSSION

The findings of this study demonstrated that human trust in AI-assisted project decision systems was shaped by a combination of explainability, perceived reliability, technological familiarity, organizational readiness, and actual decision experience. The final sample of 527 participants from 46 organizations showed moderate-to-high trust alongside substantial verification, indicating that trust did not translate into unconditional acceptance. Human trust averaged 3.71, verification behavior 3.81, and reliance 3.47, while behavioral intention exceeded actual usage, confirming the intention–behavior gap reported in earlier technology-adoption studies (Meske & Bunde, 2020). Explainability was strongly associated with trust at $r = .64$, transparency at $r = .61$, and perceived reliability at $r = .68$. These relationships were consistent with earlier research showing that understandable reasoning, predictable system behavior, visible evidence, and stable performance increase confidence in AI-supported decisions. Multivariable analysis further showed that explainability remained an independent predictor of trust at $\beta = .36$ after professional experience, digital literacy, AI familiarity, organizational characteristics, and perceived risk were controlled. Trust was subsequently associated with behavioral

intention, recommendation acceptance, actual usage, and managerial reliance, while mediation analysis showed that trust partially transmitted the effect of explainability on adoption. These findings supported earlier studies that positioned trust between technological transparency and behavioral acceptance, but they also demonstrated that adoption and reliance were not equivalent (Schmidt et al., 2020). The strongest evidence emerged from the comparison of human-only, AI-only, conventional AI-assisted, and explainable AI-assisted decision conditions. Decision accuracy increased from 73.8% under human-only decision making to 79.3% for AI-only recommendations, 82.1% for conventional AI assistance, and 86.4% for explainable AI assistance. Error rates declined correspondingly from 26.2% to 13.6%, while benchmark agreement increased from 73.1% to 88.0%. Explainable AI also achieved the highest forecasting accuracy, risk-identification accuracy, resource-allocation effectiveness, and decision consistency. These findings were consistent with earlier studies demonstrating the value of human-AI complementarity, while also challenging assumptions that AI-only systems necessarily provide the strongest performance (Shin, 2021). AI-only decisions were faster, but explainable AI-assisted decisions achieved a better balance between speed, contextual judgment, and objective accuracy. The large experimental-condition effect, partial $\eta^2 = .239$, and the difference of 12.6 percentage points between explainable AI and human-only conditions with Cohen's $d = 1.50$ confirmed that the performance improvements were practically meaningful rather than merely statistically significant.

Figure 11: Human-AI Decision-Making Framework



The findings further demonstrated that calibrated reliance, rather than maximum trust or maximum automation, was the strongest behavioral mechanism underlying superior managerial decision quality. Explainable AI-assisted participants accepted 90.6% of correct recommendations but only 13.2% of erroneous recommendations, whereas inappropriate acceptance of erroneous advice reached 28.7% in the AI-only condition (Knapič et al., 2021). Corrective overrides under explainable AI reached 71.6%, and unnecessary rejection of correct advice declined to 9.4%. These results were consistent with earlier research on automation bias and algorithm aversion, but they provided stronger evidence that explainability can reduce both over-reliance and under-reliance simultaneously. Verification frequency was highest under explainable AI at 72.4%, demonstrating that greater trust and acceptance could coexist with stronger managerial scrutiny. The interaction between system accuracy and reliance, $\beta = .23$, confirmed that reliance improved performance primarily when recommendations were technically

reliable. Subgroup findings also showed that AI familiarity, digital literacy, training, governance strength, digital maturity, project complexity, and institutional readiness materially influenced outcomes. Participants with high AI familiarity achieved decision accuracy of 85.2% compared with 73.6% among low-familiarity users, while trained participants achieved 82.9% compared with 74.8% among untrained participants (Madhav & Tyagi, 2022). High-digital-maturity organizations achieved 85.6% accuracy compared with 72.8% in low-maturity organizations, and strong-governance environments reached 85.9%. High-risk and highly complex projects generated greater verification and more conservative reliance, indicating that managers adjusted behavior according to decision consequences. Cross-country comparisons showed similar patterns, with technologically advanced environments achieving stronger overall performance while stronger accountability structures encouraged greater verification rather than blind dependence. The integrated model explained 49.9% of the variance in managerial decision quality, with calibrated reliance emerging as the strongest predictor at $\beta = .29$. Explainability, trust, governance maturity, digital readiness, adoption, AI familiarity, project complexity, and decision risk also contributed independently (Jia et al., 2018). Logistic models showed that explainability increased the odds of recommendation acceptance by 1.84 and the odds of correctly overriding erroneous advice by 2.11. The accurate-decision model achieved 81.7% classification accuracy and a ROC-AUC of .86. Robustness analyses further confirmed the stability of these results because multicollinearity remained acceptable, influential observations affected coefficients minimally, missing-data procedures produced consistent estimates, and alternative specifications generated adjusted R^2 values between .471 and .493. Collectively, these findings extended earlier research by integrating explainability, calibrated trust, actual adoption, reliance behavior, organizational conditions, and objective decision outcomes within a single analytical structure (Tillmann et al., 2020). The evidence indicated that effective human-AI collaboration depended on managers understanding system reasoning, evaluating uncertainty, accepting reliable recommendations, challenging erroneous outputs, and retaining sufficient professional oversight to combine algorithmic capability with contextual judgment (Howard & Sylvan, 2020).

CONCLUSION

This study concluded that human trust in AI-assisted project decision systems was most effective when it was calibrated to system capability rather than maximized without regard to accuracy, transparency, or contextual suitability. The findings demonstrated that explainability, perceived reliability, trust, adoption, managerial reliance, organizational readiness, governance maturity, AI familiarity, and project conditions jointly shaped managerial decision quality. Explainability showed a strong positive relationship with trust, while perceived reliability emerged as one of the most influential foundations of confidence in AI-supported recommendations. Trust was positively associated with behavioral intention, actual usage, recommendation acceptance, and reliance, yet the results also established that adoption alone did not guarantee superior decision performance. The strongest outcomes occurred when managers used AI recommendations selectively and retained sufficient oversight to distinguish reliable from erroneous advice. Explainable AI-assisted decision making produced the highest overall performance, with decision accuracy reaching 86.4%, compared with 82.1% for conventional AI-assisted decisions, 79.3% for AI-only recommendations, and 73.8% for human-only decision making. The explainable AI condition also achieved the lowest error rate, the highest benchmark agreement, and the strongest forecasting, risk-identification, and resource-allocation performance. Importantly, participants in this condition accepted 90.6% of correct AI recommendations while accepting only 13.2% of erroneous advice, indicating stronger trust calibration and reduced exposure to automation bias. The integrated model explained 49.9% of the variance in managerial decision quality, with calibrated reliance emerging as the strongest independent predictor. Organizational and individual differences further demonstrated that high AI familiarity, digital literacy, formal training, strong governance, and advanced digital maturity were associated with stronger decision performance, whereas greater project complexity and decision risk increased the need for verification and cautious reliance. Robustness analyses confirmed that these relationships remained stable across alternative model specifications, parametric and nonparametric procedures, missing-data treatments, and sensitivity checks. Overall, this study established that effective AI-assisted project decision making depended on the interaction between technological capability and disciplined managerial judgment.

Explainability supported trust, trust supported adoption, and adoption contributed to decision quality only when managers relied on AI in a calibrated, context-sensitive, and accountable manner. Human-AI collaboration therefore performed best when algorithmic analysis strengthened, rather than displaced, professional judgment, verification, responsibility, and contextual understanding.

RECOMMENDATIONS

Based on the findings of this study, organizations implementing AI-assisted project decision systems should prioritize explainable, reliable, and managerially controllable AI architectures rather than pursuing automation intensity as the principal indicator of technological advancement. AI systems used for project cost estimation, scheduling, procurement, resource allocation, risk assessment, and performance monitoring should provide clear explanations of influential variables, confidence levels, assumptions, uncertainties, and relevant decision logic so that managers can evaluate recommendations before incorporating them into final decisions. Particular attention should be directed toward calibrated reliance because the findings demonstrated that explainable AI-assisted participants achieved 86.4% decision accuracy, accepted 90.6% of correct recommendations, and accepted only 13.2% of erroneous recommendations. Organizations should therefore establish verification protocols that require additional managerial review when model confidence is low, project complexity is high, decision consequences are substantial, or AI recommendations conflict with established project evidence. Human oversight should remain clearly defined, with final accountability assigned to appropriately authorized managers for high-impact decisions. Formal AI training should also become an important component of managerial capability development because trained participants achieved substantially stronger decision performance than untrained participants. Training should address AI literacy, interpretation of explanations, uncertainty assessment, model limitations, data-quality evaluation, automation bias, algorithm aversion, appropriate override behavior, and practical verification techniques rather than focusing exclusively on software operation. Organizations with lower digital maturity should strengthen data infrastructure, system interoperability, information quality, technical support, leadership commitment, and analytical capabilities before expanding dependence on AI-supported decisions. Governance mechanisms should include documented responsibilities, access controls, model-performance monitoring, decision logs, explanation records, periodic validation, escalation procedures, and systematic review of accepted and overridden recommendations. Managers should also evaluate AI effectiveness through objective indicators such as decision accuracy, error rates, forecasting performance, risk-identification accuracy, resource-allocation effectiveness, benchmark agreement, and decision time instead of relying exclusively on adoption rates or user satisfaction. Because calibrated reliance emerged as the strongest independent predictor of decision quality, performance monitoring should specifically distinguish appropriate acceptance, unnecessary rejection, corrective overrides, and inappropriate acceptance of erroneous recommendations. Organizations operating across different industries, countries, regulatory environments, and project-risk categories should adapt governance and explanation requirements to contextual conditions rather than applying identical AI decision procedures universally. Overall, managerial AI implementation should be designed around a human-AI collaboration model in which transparent algorithmic analysis, continuous validation, organizational governance, technological competence, and accountable professional judgment operate together to improve project decision quality while limiting over-reliance, under-reliance, and automation-related errors.

LIMITATIONS

This study contained several limitations that should be considered when interpreting the relationships among explainability, human trust, AI adoption, managerial reliance, and project decision quality. First, although the final analytical sample included 527 participants from 46 organizations and represented multiple managerial roles, industries, organizational sizes, ownership structures, and project environments, the sample could not fully represent every population of managers using AI-assisted project decision systems. Differences in organizational culture, technological capability, professional responsibilities, and AI implementation practices may have influenced participant responses and restricted the broader generalizability of some subgroup results. Second, several constructs, including perceived explainability, transparency, trust, usefulness, perceived risk,

behavioral intention, governance maturity, and organizational digital readiness, were measured partly through self-reported scales. Although internal consistency was strong, with Cronbach's alpha values ranging from .82 to .93, self-reported measures remained susceptible to recall limitations, response tendencies, and differences between perceived and actual behavior. Third, the structured decision scenarios improved experimental comparability but could not reproduce the complete complexity of real project environments, where managerial decisions may involve incomplete information, stakeholder conflicts, contractual restrictions, financial pressure, regulatory requirements, rapidly changing conditions, and extended decision periods. Fourth, objective performance indicators such as decision accuracy, forecasting accuracy, risk-identification performance, resource-allocation effectiveness, and benchmark agreement depended on predefined reference outcomes; consequently, these benchmarks may not capture every legitimate managerial interpretation of complex project situations. Fifth, although the study compared human-only, AI-only, conventional AI-assisted, and explainable AI-assisted conditions, the results were dependent on the particular AI recommendations, explanation formats, decision tasks, and accuracy levels incorporated into the experimental design. Different algorithms or explanation interfaces could produce different trust and reliance patterns. Sixth, the cross-sectional components of the research limited the ability to establish how trust, adoption, verification, and reliance changed after prolonged system exposure or repeated AI errors. Seventh, cross-country and regional comparisons were interpreted through broader technological-readiness and institutional categories, which may have obscured important differences among individual countries, regulatory systems, and cultural environments.

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