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RESEARCH ARTICLE

HUMAN–AI COLLABORATION AND STRATEGIC DECISION QUALITY: A CONCEPTUAL MODEL AND MEASUREMENT FRAMEWORK

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ABSTRACT

Artificial intelligence is increasingly incorporated into strategic analysis and managerial decision-making, raising questions about the conditions under which human–AI collaboration supports decision quality. This conceptual paper develops a framework connecting human–AI collaboration, managerial AI literacy, AI governance mechanisms, and trust calibration with strategic decision quality. It focuses on a manager's evaluation of a specific AI-supported strategic decision, distinguishing decision quality from subsequent organisational performance. The paper adopts a theory-development approach based on a critical integration of literature on managerial judgment, human–AI collaboration, and organisational governance. The proposed framework positions human–AI collaboration, managerial AI literacy, governance mechanisms, and trust calibration as explanatory constructs. Trust calibration is additionally proposed to moderate the relationship between human–AI collaboration and strategic decision quality, reflecting the importance of aligning reliance on AI recommendations with their task-specific reliability. The framework is expressed through a proposed regression specification and accompanied by construct definitions, candidate measurement indicators, and a protocol for future empirical testing. Particular attention is given to distinguishing perceived decision quality from independently assessed quality, and self-reported trust calibration from observable reliance behaviour. No empirical data are analysed, and the proposed relationships remain untested. The intended contribution is an operationally explicit account of how managerial capabilities, governance arrangements, and calibrated reliance may jointly shape AI-supported strategic decisions. The framework also offers a basis for examining managerial training, review procedures, and accountability in strategic decision processes.

Keywords: *Human–AI collaboration; Strategic decision quality; Managerial AI literacy; AI governance; Trust calibration; Conceptual model.*

JEL: *M15; M12; D81; D83.*

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1. Introduction

Artificial intelligence (AI) is becoming part of the analytical processes through which managers interpret information, evaluate alternatives, and formulate strategic choices. Its organisational relevance extends beyond the automation of routine activities to the support of decisions involving uncertainty, competing objectives, and incomplete information. However, the availability of AI-generated recommendations does not establish that managers will interpret or use them appropriately. Understanding AI-supported strategic decision-making therefore requires attention to the interaction between technological capabilities, managerial judgment, and the organisational arrangements governing their use.

Research on human–AI collaboration provides a foundation for examining this interaction. Jarrahi (2018) conceptualises human–AI symbiosis in organisational decision-making through the complementary contributions of computational analysis and human judgment. Raisch and Krakowski (2021) further explain that automation and augmentation are interdependent, creating managerial tensions that cannot be resolved by treating human involvement and technological substitution as separate choices. These perspectives suggest that the value of AI depends partly on how responsibilities and analytical activities are organised within the decision process.

Nevertheless, combining human and artificial intelligence does not consistently produce superior performance. In their systematic review and meta-analysis, Vaccaro et al. (2024) find that human–AI combinations, on average, underperform the better of humans or AI acting alone, while documenting substantial variation across tasks and conditions. These findings challenge the assumption that collaboration necessarily creates complementarity. For strategic management, they motivate a more specific question: which managerial and organisational conditions help translate AI-supported collaboration into better decisions?

Managerial AI literacy represents one relevant condition. Pinski et al. (2024) examine top management team AI literacy in relation to corporate AI orientation and implementation ability, establishing its relevance to organisational value creation with AI. Their analysis concerns team-level characteristics and firm-level outcomes. The present paper focuses instead on the decision episode, proposing that a manager's ability to interpret AI outputs, recognise their limitations, and assess their relevance may help explain differences in strategic decision quality. This proposed relationship extends the discussion to a more immediate decision outcome and requires independent empirical testing.

Trust calibration provides a further basis for explaining variation in collaboration outcomes. Lee and See (2004) connect trust in automation with appropriate reliance, emphasising the importance of context and system characteristics. Building on this perspective, the present study distinguishes calibrated trust from a generally favourable attitude towards AI. Calibration concerns whether reliance corresponds to the system's demonstrated capabilities and limitations in a particular task. Accordingly, greater trust is not

assumed to be inherently beneficial. The framework proposes that better calibration strengthens the relationship between human–AI collaboration and strategic decision quality.

The strategic context also requires explicit consideration. Srinivas and Chetan (2026) examine how top management teams integrate AI into strategic decision-making, identifying problem structuredness and situational predictability as important contextual dimensions. Their findings demonstrate that strategic AI integration is already an active research area. The present paper addresses a narrower explanatory task: specifying how collaboration, managerial AI literacy, governance mechanisms, and trust calibration can be connected within a testable model of decision quality. It proposes that governance arrangements—including review responsibilities, documentation requirements, and procedures for questioning recommendations—may provide conditions under which managers can assess and use AI outputs more effectively. This governance relationship is advanced as a theoretical proposition rather than an established empirical result.

Against this background, the paper addresses the following research question: How do human–AI collaboration, managerial AI literacy, and AI governance relate to strategic decision quality, and how does trust calibration condition the relationship between collaboration and decision quality?

The paper develops a conceptual model in which strategic decision quality is the outcome of interest. The unit of analysis is a specific AI-supported strategic decision evaluated by a participating manager. This boundary distinguishes the quality of the decision from subsequent organisational performance, which may also reflect implementation conditions and external events. Human–AI collaboration is defined by the organisation of joint analytical work and the integration of human and AI contributions, rather than by whether the resulting decision is successful.

The intended contribution comprises a set of theoretically argued relationships and an accompanying measurement framework. The paper specifies construct boundaries, proposes a regression formulation for future testing, and distinguishes self-reported perceptions from behavioural or independently assessed measures. It does not estimate coefficients or claim empirical validation. By connecting conceptual development with operational definitions, the study provides a basis for investigating when AI-supported collaboration may improve strategic decision quality.

2. Theoretical Background and Conceptual Foundations

2.1. Human–AI Collaboration and Strategic Decision Quality

Human–AI collaboration concerns the organisation of work in which human decision-makers and AI systems contribute to a shared task. In strategic decision-making, these contributions may involve identifying relevant information, generating alternatives, examining assumptions, and comparing possible consequences. Collaboration is therefore more specific than AI adoption: an organisation may possess AI tools without integrating their outputs meaningfully into managerial deliberation. Jarrahi (2018) explains the potential complementarity between AI's analytical capabilities and human capacities for contextual interpretation and judgment. This perspective is relevant to strategic decisions, where the information available rarely provides an uncontested basis for action. AI may support the examination of patterns and alternatives, while managers interpret their relevance to organisational objectives and circumstances. Complementarity, however, remains a potential property of the interaction rather than an automatic consequence of using both forms of intelligence.

Raisch and Krakowski (2021) provide a further theoretical foundation through the automation–augmentation paradox. Their argument challenges the treatment of automation and augmentation as independent managerial choices. Applied to strategic decision episodes, this perspective directs attention to how analytical responsibilities are distributed and adjusted. A manager may delegate information processing to AI while retaining responsibility for interpreting recommendations and selecting a course of action. The resulting decision process depends on how these contributions are connected, including whether opportunities exist to question or revise AI-generated analysis.

The distinction between collaboration and successful collaboration is essential to the proposed model. Vaccaro et al. (2024) document heterogeneous performance effects across human–AI combinations, indicating that the presence of both contributors does not establish an advantage over the better-performing contributor alone. Accordingly, the present framework defines collaboration through observable features of joint work, such as the integration of contributions and opportunities for iterative exchange. It excludes decision success from the definition of collaboration itself, preventing the explanatory construct from incorporating the outcome it is intended to explain. Strategic decision quality also requires a clear boundary. Dean and Sharfman (1996) examine the relationship between strategic decision processes and decision effectiveness, providing a foundation for considering how decisions are reached alongside their consequences. The present framework adopts a narrower, decision-time interpretation of quality: the extent to which the selected course of action is defensible given the available evidence, relevant alternatives, explicit uncertainties, and strategic objectives. Subsequent organisational performance remains a separate outcome because implementation and external developments can influence what follows a decision.

This distinction has measurement implications. A manager's satisfaction with a decision is not sufficient evidence of its quality. Future assessment should consider the justification for the selected alternative, the treatment of conflicting evidence, and consistency with stated objectives. These dimensions represent candidate assessment criteria rather than a validated scale. They should be evaluated against decision records or independent ratings where feasible, with self-reported quality identified explicitly when used. The integration of AI contributions also requires substantive engagement with their underlying limitations. In a study of medical diagnosis, Lebovitz et al. (2022) examine how professionals engage with opaque AI when making critical judgments. Although this setting differs from strategic management, it draws attention to the interpretative work required when users cannot readily inspect how recommendations are produced. This supports examining collaboration through actual engagement with AI analysis rather than tool use alone.

The framework consequently proposes a conditional argument: human–AI collaboration may improve strategic decision quality when the interaction brings relevant analytical contributions into managerial deliberation. The strength of this relationship is expected to depend on whether managers can judge when AI recommendations deserve reliance. Task characteristics must also be considered. Srinivas and Chetan (2026) identify problem structuredness and situational predictability as important dimensions of strategic AI integration, supporting the need to specify the decision context when testing the proposed relationships.

2.2. Managerial AI Literacy, Governance and Trust Calibration

Managerial AI literacy concerns the knowledge and evaluative abilities required to engage critically with AI-supported work. It does not require managers to possess the technical expertise of system developers. Within this framework, it refers to understanding the purpose and limitations of the AI application,

interpreting its outputs, and recognising when additional evidence or specialist assessment is needed. Pinski et al. (2024) establish the strategic relevance of top management team AI literacy by examining its relationships with corporate AI orientation and implementation ability. Their study addresses team-level literacy and organisational characteristics. The present framework draws on this work while proposing a different relationship at the decision-episode level: managers with stronger AI literacy may be better equipped to interpret the relevance and limitations of AI-generated recommendations. This extension remains a proposition to be tested and should not be treated as a finding of the earlier study.

AI literacy is conceptually distinct from both collaboration and trust calibration. Literacy concerns what the manager understands and can evaluate; collaboration concerns how human and AI contributions are organised; calibration concerns whether the manager's trust is appropriate to the system's capabilities in the task. A knowledgeable manager may operate within a poorly designed collaboration process, while frequent AI use may occur without a sufficient understanding of system limitations. Maintaining these boundaries is necessary for meaningful measurement and interpretation. Long and Magerko (2020) conceptualise AI literacy through competencies supporting critical evaluation, communication, and effective interaction with AI. This provides a foundation for distinguishing managerial AI literacy from technical familiarity or self-confidence. The proposed AIL construct applies this evaluative perspective to a specific strategic decision episode. Trust likewise requires a differentiated treatment. Glikson and Woolley (2020) review empirical research on the determinants of human trust in AI, providing context for examining how trust develops across applications. Complementing this perspective, Buçinca et al. (2021) demonstrate that cognitive forcing functions can reduce overreliance in an AI-assisted decision task. These findings support attention to critical engagement, although their transfer to strategic decision-making requires testing. The present framework therefore distinguishes trust calibration from general trust and proposes its moderating relationship as an open empirical question.

Organisational AI governance provides the structural context for these individual activities. Mäntymäki et al. (2022) position AI governance within organisational governance and connect it to arrangements that guide AI use in accordance with organisational objectives and responsibilities. Building on this foundation, the proposed model focuses on governance mechanisms that apply to the particular decision episode, including assigned review responsibilities, documentation of AI contributions, and procedures for escalating questionable recommendations.

The relevant construct is the implementation of these mechanisms, rather than the existence of a policy alone. A formal review requirement may contribute little if decision-makers lack the authority, information, or time needed to exercise it. The framework therefore proposes that enacted governance can support decision quality by making scrutiny possible and responsibility identifiable. This relationship is not assumed to increase indefinitely with additional controls: disproportionate procedures may delay decisions or encourage superficial compliance.

Trust calibration addresses a different aspect of AI-supported judgment. Lee and See (2004) explain trust in automation in relation to appropriate reliance, providing a foundation for distinguishing justified dependence from indiscriminate acceptance. For the present framework, calibrated trust means that a manager's confidence in AI corresponds reasonably to its demonstrated task-specific capabilities and limitations. Observable acceptance or rejection of recommendations provides evidence about reliance, but it does not, by itself, fully measure the underlying trust judgment.

This distinction explains the proposed moderating role of calibration. Collaboration creates opportunities for AI outputs to influence deliberation; calibration may determine whether that influence is appropriate.

When calibration is stronger, managers should be better positioned to retain useful recommendations and question unreliable ones. When calibration is weak, additional interaction may amplify errors or leave useful analytical contributions unused. The proposed interaction thus concerns the conditions under which collaboration contributes to quality, rather than an assumption that greater trust always improves decisions.

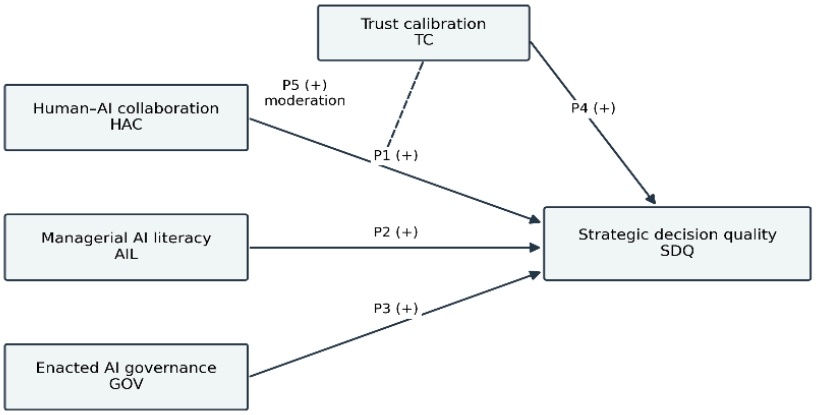
Taken together, these constructs offer complementary explanations at the decision-episode level. Collaboration describes the arrangement of joint work, literacy captures managerial evaluative capability, governance captures the review arrangements applied to the decision, and calibration captures the appropriateness of trust. The following model-development section translates these distinctions into research propositions and a regression specification for future empirical assessment.

3. Conceptual Model and Research Propositions

3.1. Model Structure and Construct Definitions

Building on the preceding theoretical discussion, the proposed model connects human–AI collaboration (HAC), managerial AI literacy (AIL), enacted AI governance (GOV), and trust calibration (TC) with strategic decision quality (SDQ). Trust calibration additionally moderates the relationship between collaboration and decision quality. Figure 1 presents these proposed relationships.

Figure 1. Proposed conceptual model



Source: Authors' conceptual development. Note: Solid arrows indicate proposed direct relationships. The dashed arrow indicates the proposed moderating role of trust calibration in the relationship between human–AI collaboration and strategic decision quality. Positive signs represent theoretical expectations, not estimated effects.

The model concerns a specific strategic decision episode in which a manager uses AI-generated analysis or recommendations. Its scope includes activities such as evaluating a market-entry option, comparing investment alternatives, or assessing a proposed organisational change. AI-supported routine decisions fall outside this scope unless they involve consequential strategic commitments. The constructs occupy distinct explanatory roles. HAC describes the arrangement of joint analytical work. AIL captures the manager's capacity to understand and evaluate AI contributions. GOV concerns the governance mechanisms actually applied to the decision episode. TC represents the correspondence between trust and

the AI system's task-specific capabilities. SDQ captures the defensibility of the selected course of action given the information and objectives available at the time.

Table 1. Construct definitions and proposed operationalisation

Construct	Acronym	Definition within the model	Candidate assessment approach
Strategic decision quality	SDQ	The defensibility of the selected strategic alternative in relation to available evidence, relevant uncertainties, and stated objectives.	Independent assessment of the decision rationale, supported by decision records; managerial perceptions reported separately.
Human–AI collaboration	HAC	The extent to which human and AI contributions are integrated through coordinated analytical work and iterative exchange.	Episode-specific indicators covering the allocation of analytical tasks, integration of contributions, and opportunities for revision.
Managerial AI literacy	AIL	The manager's ability to understand the application's purpose, interpret its outputs, and recognise relevant limitations.	Knowledge questions and scenario-based interpretation tasks, supplemented by self-assessment.
Enacted AI governance	GOV	The extent to which review, documentation, responsibility, and escalation arrangements are applied to the focal decision.	Decision records, procedural evidence, and episode-specific reports of mechanisms actually used.
Trust calibration	TC	The correspondence between the manager's trust judgments and the AI system's demonstrated capabilities and limitations in the task.	Repeated confidence judgments compared with demonstrated system reliability, supplemented by acceptance and rejection behaviour.

Note: These are proposed operationalisation routes, not validated scales. Construct dimensionality and the suitability of reflective, formative, or composite measurement require evaluation before estimation.

Measurement should preserve these boundaries. HAC indicators should not describe successful outcomes, because doing so would incorporate decision quality into its proposed predictor. AIL should not be measured solely through confidence in using AI. Similarly, GOV should capture enacted arrangements rather than general awareness of organisational policies. TC requires an external reference to system capability; self-reported caution alone cannot establish that trust is calibrated.

3.2. Research Propositions

The first proposed relationship concerns the integration of human and AI contributions. Joint analytical work may broaden the information considered and support comparison between computational recommendations and managerial interpretation. However, the model does not assume that increasing AI use necessarily improves decisions. The proposition concerns collaboration within an appropriately specified strategic task, with its association evaluated at an explicitly defined reference level of trust calibration.

P1. Human–AI collaboration is positively associated with strategic decision quality at the specified reference level of trust calibration. Managerial AI literacy may support decision quality by helping managers recognise the relevance, assumptions, and limitations of AI-generated analysis. This capability can help prevent technically plausible outputs from being accepted without considering their suitability for the strategic problem.

P2. Managerial AI literacy is positively associated with strategic decision quality, holding the other modelled constructs constant. Enacted governance may support decision quality by establishing who reviews AI contributions, what must be documented, and how questionable recommendations are challenged. This proposition concerns proportionate and usable arrangements; it does not imply that additional procedural requirements are always beneficial.

P3. Enacted AI governance is positively associated with strategic decision quality within the range of proportionate governance arrangements. Trust calibration may contribute to decision quality by aligning managerial confidence with the demonstrated strengths and limitations of the AI application. Unlike general trust, calibration does not imply consistently accepting or consistently rejecting AI recommendations.

P4. Trust calibration is positively associated with strategic decision quality at the specified reference level of human–AI collaboration. The moderating proposition concerns whether calibration changes the contribution of collaboration. When trust is appropriately calibrated, managers may be better positioned to incorporate useful recommendations and question unreliable ones. Collaboration under poorly calibrated trust may instead increase the influence of unsuitable analysis or leave useful contributions unexploited.

P5. Trust calibration positively moderates the relationship between human–AI collaboration and strategic decision quality, such that the association becomes more positive as calibration improves.

Table 2. Summary of proposed relationships and analytical interpretation

Proposition	Proposed relationship	Expected direction	Interpretation in future testing
P1	HAC → SDQ	Positive at the TC reference value	Conditional association between collaboration and decision quality.
P2	AIL → SDQ	Positive	Association between managerial AI literacy and decision quality, holding other included variables constant.
P3	GOV → SDQ	Positive within the stated scope	Association between enacted, proportionate governance and decision quality.
P4	TC → SDQ	Positive at the HAC reference value	Conditional association between calibration and decision quality.
P5	HAC × TC → SDQ	Positive interaction	The HAC–SDQ association becomes more positive as calibration increases.

Note: The reference values of HAC and TC must be specified before interpreting the main effects. Mean-centering is one possible approach, in which each reference value corresponds to the sample mean. All relationships remain theoretical propositions.

The framework provides a deliberately bounded specification. It does not exclude additional relationships, such as AI literacy influencing collaboration or governance supporting calibration. Those pathways represent possible extensions requiring separate theoretical justification. The initial model focuses on the proposed direct associations and the collaboration–calibration interaction to maintain a clear basis for operationalisation and future testing.

4. Methodological Approach and Model Specification

4.1. Conceptual Research Design

This study adopts a conceptual research design to examine how human–AI collaboration, managerial AI literacy, enacted AI governance, and trust calibration may contribute to strategic decision quality. No primary data are collected. The model and its proposed relationships are developed for future empirical testing. The unit of analysis is a specific strategic decision episode involving AI-supported analysis and a manager who participates directly in evaluating its contribution. Decision quality is assessed against the evidence, uncertainties, and strategic objectives available when the decision was made.

4.2. Proposed Conceptual Regression Model

The proposed model is expressed as:

$$Y_{(SDQ)} = X_0 + X_{1(HAC)} + X_{2(AIL)} + X_{3(GOV)} + X_{4(TC)} + X_{5(HAC \times TC)} + \varepsilon$$

$Y_{(SDQ)}$ represents strategic decision quality, and X_0 is the constant. $X_{1(HAC)}$, $X_{2(AIL)}$, $X3_{(GOV)}$, and $X_{4(TC)}$ represent the weighted contributions of the explanatory variables. $X_{5(HAC \times TC)}$ represents the weighted contribution of their specified interaction. The weights would be determined through empirical estimation; the model does not assume equal contributions.

Table 3. Definition of the model components

Component	Meaning	Role in the model
Y(SDQ)	Strategic decision quality	Dependent variable: the defensibility of the selected alternative given available evidence, uncertainties, and strategic objectives.
X0	Constant	Baseline value determined by the coding and reference values of the explanatory variables.
X1(HAC)	Human–AI collaboration	Weighted contribution associated with coordinating and integrating human judgment and AI-generated analysis.
X2(AIL)	Managerial AI literacy	Weighted contribution associated with understanding, interpreting, and critically evaluating AI outputs.
X3(GOV)	Enacted AI governance	Weighted contribution associated with review, documentation, responsibility, and escalation mechanisms applied to the decision.
X4(TC)	Trust calibration	Weighted contribution associated with aligning managerial trust with AI's demonstrated task-specific capabilities.
X5(HAC × TC)	Collaboration–calibration interaction	Weighted contribution associated with calibration changing the relationship between collaboration and decision quality.

ε	Error term	Variation in decision quality not explained by the model.

Source: Authors' conceptual development.

$X_{1(HAC)}$ concerns how human and AI contributions are integrated into strategic deliberation. Its underlying variable captures task coordination and iterative exchange, independently of whether the resulting decision is successful; $X_{2(AIL)}$ concerns the manager's ability to understand the application's purpose, interpret its outputs, and recognise limitations relevant to the decision. Its underlying variable distinguishes demonstrated competence from confidence or frequency of AI use; $X_{3(GOV)}$ concerns governance mechanisms actually applied during the decision episode. These include assigned review responsibilities, documentation of AI contributions, and procedures for challenging questionable recommendations. The proposed contribution concerns proportionate arrangements that support substantive review; $X_{4(TC)}$ concerns the correspondence between managerial trust and the AI system's demonstrated capabilities. Its underlying variable captures appropriate trust rather than assuming that greater confidence necessarily improves decisions; $X_{5(HAC \times TC)}$ expresses the proposed moderating relationship. The model proposes that the association between collaboration and decision quality becomes more positive as calibration improves. Consequently, $X_{1(HAC)}$ must be interpreted at a specified reference level of calibration, while $X_{4(TC)}$ must be interpreted at a specified reference level of collaboration. Together, these contributions explain variation in Y(SDQ), subject to the model's scope conditions. The error term, ε, acknowledges additional influences outside the initial specification.

4.3. Proposed Operationalisation

Future empirical research must measure the underlying variables before estimating their weighted contributions. Table 4 connects the model notation with candidate assessment procedures.

Table 4. Proposed operationalisation of the model components

Component	Assessment focus	Candidate procedure
$Y_{(SDQ)}$	Defensibility of the strategic decision	Independent assessment of decision records against criteria covering evidence, uncertainty, and strategic objectives.
$X_{1(HAC)}$	Coordination and integration of human and AI inputs	Episode-specific questions and records describing task allocation, exchange, and revision.
$X_{2(AIL)}$	Managerial understanding and evaluation of AI	Knowledge questions and interpretation tasks, supplemented by self-assessment.
$X_{3(GOV)}$	Governance arrangements enacted during the episode	Evidence of review, documentation, responsibility, and escalation procedures actually used.
$X_{4(TC)}$	Correspondence between trust and demonstrated capability	Comparison of confidence judgments with independently established task-specific AI reliability.
$X_{5(HAC \times TC)}$	Joint variation in collaboration and calibration	Interaction constructed from the measured collaboration and calibration variables before estimating its contribution.

Note: These procedures guide instrument development and have not been empirically validated.

Measurement development should include content assessment, cognitive interviewing, and pilot evaluation. The variables underlying $X_{1(HAC)}$, $X_{2(AIL)}$, $X_{3(GOV)}$, and $X_{4(TC)}$ must remain distinguishable from

one another and from $Y_{(SDQ).}$ In particular, collaboration should not be defined through successful outcomes, literacy should not be inferred solely from confidence, and governance should not be inferred solely from written policies. Calibration requires an independent reference to demonstrated AI capability. Decision quality should preferably be assessed independently of the manager's general satisfaction and subsequent organisational performance.

The estimation method should follow the measurement structure and sampling design. Linear regression may be appropriate for defensible, approximately continuous scores. Other approaches may be required for ordinal outcomes, latent constructs, or repeated decisions within managers and organisations. The model remains untested. Future research would determine the magnitude, direction, and uncertainty of each contribution and assess whether $X_{5(HAC \times TC)}$ supports the proposed moderation. Observational associations alone would not establish causal effects.

5. Discussion and Implications

The proposed model explains strategic decision quality through the combined contributions of human–AI collaboration, managerial AI literacy, enacted governance, and trust calibration. Its central argument is that AI-supported collaboration creates opportunities for improvement whose realisation depends on managerial capabilities and the conditions governing AI use. This interpretation connects the complementary roles of human judgment and computational analysis with the managerial tensions surrounding automation and augmentation (Jarrahi, 2018; Raisch & Krakowski, 2021).

The contribution represented by $X_{1(HAC)}$ should therefore be interpreted conditionally. Human–AI interaction does not necessarily improve decisions, as demonstrated by the heterogeneous performance effects reported by Vaccaro et al. (2024). The model proposes that $X_{2(AIL)}$ and $X_{3(GOV)}$ help explain this variation through managerial evaluative competence and the review arrangements applied to the decision. Whereas Pinski et al. (2024) examine AI literacy in relation to organisational AI orientation and implementation ability, the present framework proposes a relationship with the quality of a specific strategic decision. This decision-level extension remains untested.

Trust calibration provides the model's principal conditional mechanism. $X_{4(TC)}$ represents the contribution associated with aligning trust with demonstrated AI capability, while $X_{5(HAC \times TC)}$ expresses the proposition that calibration strengthens the collaboration–quality relationship. Following the appropriate-reliance perspective of Lee and See (2004), the objective is not to maximise trust, but to support confidence that corresponds to the system's task-specific strengths and limitations.

For managers, the framework suggests evaluating how AI analysis is interpreted and incorporated into decisions, rather than treating frequent use as evidence of value. Practical applications include training managers to examine assumptions and uncertainty, assigning clear review responsibilities, and documenting consequential AI contributions. Feedback on reliable and unreliable recommendations may also help managers revise their expectations. These applications follow from the conceptual argument and are not demonstrated interventions.

The distinction between $Y_{(SDQ)}$ and subsequent organisational performance is equally important. A defensible decision may produce an unfavourable outcome because circumstances change, while a poorly justified decision may benefit from favourable events. Decision quality should therefore be assessed against the evidence and objectives available when the choice was made.

The model's limitations arise primarily from its untested status and measurement requirements. Collaboration, literacy, governance, and calibration must be distinguished empirically, and calibration requires credible benchmarks of AI capability. Independent assessment of $Y_{(SDQ)}$ also requires explicit criteria and access to decision records. Future research should test the proposed relationships, consider alternative pathways between the explanatory variables, and examine contextual differences. In particular, problem structuredness and situational predictability warrant attention because they shape strategic AI integration (Srinivas & Chetan, 2026). The framework's intended contribution is a testable explanation and measurement basis, rather than an established predictive model.

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