Beyond the Black Box: A Human-Centered Framework for Explainable Artificial Intelligence in Enterprise Decision Making

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Abstract

The accelerating deployment of artificial intelligence within enterprise decision environments has intensified scholarly and managerial concern over the opacity of algorithmic reasoning. This paper examines how human-centered explainable artificial intelligence (XAI) can reconcile the analytical power of machine learning with the interpretive, ethical, and accountability requirements of organizational decision making. Employing a qualitative, theory-driven synthesis of peer-reviewed literature spanning computer science, information systems, and organizational behavior, the study integrates technical scholarship on interpretability methods with human-computer interaction research on trust, cognition, and algorithm aversion. The analysis is structured around a conceptual framework that positions explanation not as a terminal technical output but as a relational process linking data, model, explanation, human judgment, and organizational action. Findings indicate that explainability functions as a boundary object between technical and managerial communities, that trust in AI-assisted decisions is calibrated rather than fixed, and that enterprise adoption of XAI is shaped as much by governance structures and workforce readiness as by algorithmic sophistication. The paper further identifies a persistent tension between model accuracy and interpretability, and demonstrates that this tension is frequently overstated in practice when explanation is treated as a design requirement rather than an afterthought. The study contributes an integrative framework for human-centered enterprise XAI, clarifies conceptual ambiguities surrounding interpretability and explainability, and offers guidance for scholars and practitioners seeking to design accountable, trustworthy, and organizationally embedded AI decision systems.

Keywords: explainable artificial intelligence; human-centered AI; enterprise decision making; algorithmic trust; interpretability; organizational adoption

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1. Introduction

Artificial intelligence has moved decisively from the periphery of enterprise computing to the center of managerial decision infrastructure. Credit approval, fraud detection, workforce scheduling, supply chain forecasting, and clinical triage now routinely incorporate machine

learning models whose internal logic is rarely legible to the managers, employees, or customers whose lives the outputs affect. This shift has produced a well-documented paradox: the very models that promise superior predictive accuracy often do so by trading away the transparency that human decision makers rely upon to justify, contest, or refine a judgment (Rudin, 2019). Enterprises adopting such systems therefore confront a governance problem as much as a technical one, since a model that cannot be explained is difficult to audit, difficult to trust, and difficult to defend when its recommendations are challenged by regulators, employees, or the public.

Explainable artificial intelligence, commonly abbreviated as XAI, has emerged as the disciplinary response to this predicament. Yet the field has historically been dominated by a computational orientation that treats explanation as a mathematical artifact to be optimized rather than a communicative act embedded in a specific organizational and psychological context (Miller, 2019). Human-centered artificial intelligence, by contrast, reframes the objective of system design around human control, comprehension, and self-efficacy, insisting that automation and human agency be treated as complementary design variables rather than competing ones (Shneiderman, 2020). The convergence of these two intellectual traditions, technical explainability and human-centered design, forms the conceptual terrain that this paper investigates. Enterprise decision making provides a particularly consequential setting for this inquiry because it combines high-stakes outcomes, distributed accountability, and heterogeneous audiences, ranging from data scientists to frontline managers to external stakeholders, each of whom requires a different register of explanation.

The problem addressed here is therefore twofold. First, there remains conceptual ambiguity in the literature regarding what an explanation must accomplish for it to be considered adequate in an organizational, rather than purely statistical, sense. Second, existing scholarship tends to treat the technical mechanics of interpretability and the organizational dynamics of trust and adoption as separate literatures, producing a fragmented understanding of how explainability actually functions once it leaves the laboratory and enters a boardroom or a call center. Frenette (2022) observes that human-centric artificial intelligence enhances decision accuracy while preserving fairness and accountability precisely because it aligns algorithmic insight with human judgment and organizational values, yet the mechanisms through which this alignment is achieved, sustained, or undermined in practice remain underspecified.

This paper pursues three interrelated objectives. The first is to synthesize the technical and human-centered strands of the explainability literature into a coherent conceptual account of what enterprise-grade explanation requires. The second is to examine, through the lens of trust calibration and organizational behavior research, how explanations shape the willingness of managers and employees to rely upon algorithmic recommendations. The third is to propose an integrative framework that situates explanation within a broader decision pipeline extending from data collection through organizational action and feedback, thereby moving beyond a

narrow, model-centric conception of explainability toward one that is genuinely enterprise-centric.

Accordingly, the study is organized around the following research questions. First, how has the conceptual understanding of explainability evolved from a narrowly technical concern toward a human-centered design principle, and what theoretical tensions remain unresolved within this evolution? Second, what mechanisms link explanation to trust, reliance, and ultimately the quality of decisions made within enterprise settings? Third, what organizational, ethical, and methodological conditions must be satisfied for human-centered XAI to be implemented responsibly and effectively within enterprise decision environments? These questions are addressed through a structured qualitative synthesis of the peer-reviewed literature, supplemented by a conceptual framework developed specifically for this study.

The theoretical grounding for the paper draws principally upon three traditions. The first is the human-centered AI framework articulated by Shneiderman (2020), which separates levels of automation from levels of human control and argues that well-designed systems can simultaneously maximize both. The second is the social-scientific account of explanation advanced by Miller (2019), which insists that useful explanations are contrastive, selective, and socially situated rather than exhaustive recitations of causal structure. The third is the trust calibration literature within human-computer interaction and behavioral decision research, including work on algorithm aversion (Dietvorst et al., 2015) and on the perceptual effects of transparency (Shin, 2021; Kizilcec, 2016). Together these traditions furnish the analytical vocabulary through which the remainder of the paper proceeds, beginning with a comprehensive review of the literature in Section 2, followed by a description of the methodological approach in Section 3, the presentation of findings in Section 4, a discussion of implications in Section 5, and concluding remarks in Section 6.

The contribution of the paper is conceptual and integrative rather than empirical in the experimental sense. Nonetheless, its practical significance is considerable. As enterprises accelerate investment in generative and predictive AI, the absence of a coherent, human-centered account of explainability leaves practitioners without adequate guidance on how to design systems that are simultaneously performant, interpretable, and organizationally trustworthy. By synthesizing dispersed strands of computer science, information systems, and organizational behavior scholarship, this paper aims to reduce that gap and to equip both researchers and practitioners with a framework capable of guiding future empirical inquiry.

2. Literature Review

2.1 From Automation to Augmentation: The Conceptual Turn Toward Human-Centered AI

The intellectual history of artificial intelligence has long oscillated between two competing ambitions: building machines that emulate human cognition and building tools that extend human capability. Shneiderman (2020) argues that much of the confusion surrounding

contemporary AI design stems from a failure to distinguish these ambitions, noting that the pursuit of humanlike autonomy often leads designers away from the comprehensible, predictable, and controllable systems that organizational users actually require. His two-dimensional framework, which separates the degree of computer automation from the degree of human control, reframes the design objective away from a zero-sum trade-off and toward the simultaneous maximization of both variables. This reframing is significant for enterprise contexts because it directly challenges the assumption, still common in engineering practice, that greater automation necessarily entails diminished human oversight.

This human-centered turn has been extended in subsequent scholarship examining how organizations can operationalize the principle of meaningful human control. Analyses of human-centered AI foundations emphasize that enterprises must redesign workflows and decision systems around transparency, participatory design, and accountability, and that this redesign requires investment in workforce reskilling so that employees can function productively within hybrid intelligence environments rather than being displaced by them. The implication is that human-centered AI is not merely an interface design philosophy but an organizational transformation agenda, one that reaches into governance structures, incentive systems, and the allocation of decision rights between humans and machines. Frenette (2022) similarly frames human-centric AI as a departure from automation-focused models, arguing that its principal advantage lies in embedding ethical considerations, bias mitigation, and contextual judgment directly into the analytical pipeline rather than treating these as downstream corrective measures.

A parallel body of work situates this shift within the broader trajectory of enterprise digital transformation. Dwivedi et al. (2021) offer a multidisciplinary account of the opportunities and challenges posed by AI adoption, cataloguing concerns that range from data governance and algorithmic bias to workforce displacement and regulatory uncertainty. Their analysis underscores that the diffusion of AI within organizations is rarely a purely technical process; it is mediated by managerial sense-making, professional norms, and institutional pressures that determine whether a technically sound system is actually trusted and used. This observation anticipates a recurring theme in the present review, namely that the success of explainable AI cannot be evaluated solely by reference to algorithmic properties but must be assessed against the organizational context into which the system is introduced.

2.2 Technical Foundations of Explainability: Interpretability, Transparency, and Post-hoc Methods

The technical literature on explainability has developed a rich, if occasionally inconsistent, vocabulary for describing how and why a model's behavior can be rendered comprehensible. Doshi-Velez and Kim (2017) were among the first to call for a rigorous science of interpretability, arguing that the field had proceeded for years without a shared definition of what interpretability means or how it should be measured. Lipton (2018) pushed this critique further, contending that interpretability is not a monolithic property but a bundle of related yet distinct desiderata, including transparency, simulatability, decomposability, and post-hoc

explainability, each of which trades off differently against predictive performance. This conceptual disaggregation matters for enterprise applications because different organizational stakeholders often require different desiderata: a compliance officer may need decomposability sufficient for audit, while a frontline manager may need only a post-hoc justification sufficient for a customer-facing conversation.

Methodologically, the field bifurcates into intrinsically interpretable models and post-hoc explanation techniques applied to opaque models. Rudin (2019) has argued forcefully that, for high-stakes decisions, organizations should favor inherently interpretable models over black-box models paired with post-hoc explanations, on the grounds that post-hoc methods can produce explanations that are plausible but unfaithful to the model's actual reasoning. This position remains contested, however, because inherently interpretable models frequently underperform more complex architectures on high-dimensional enterprise data such as transactional histories or unstructured text. The dominant practical response within industry has therefore been the proliferation of model-agnostic post-hoc techniques, most notably Local Interpretable Model-Agnostic Explanations, or LIME (Ribeiro et al., 2016), and SHapley Additive exPlanations, or SHAP (Lundberg & Lee, 2017).

LIME approximates the behavior of a complex model in the local neighborhood of a specific prediction by fitting an interpretable surrogate model, typically a sparse linear model, to perturbed samples drawn around the instance of interest. SHAP, by contrast, draws on cooperative game theory to allocate a prediction's outcome fairly among its contributing features using Shapley values, offering a theoretically grounded and locally consistent attribution of feature importance. Both techniques have become de facto standards in enterprise machine learning pipelines because they are model-agnostic and therefore compatible with the heterogeneous model stacks common in large organizations. Adadi and Berrada (2018), in a widely cited survey, catalogue the proliferation of such techniques and observe that the field's rapid technical growth has outpaced its conceptual clarity regarding what constitutes a good explanation for a given audience and purpose.

Arrieta et al. (2020) attempt to resolve some of this conceptual fragmentation by proposing a taxonomy that links explainability techniques to the broader goal of responsible AI, arguing that explainability should be understood as one pillar within a larger constellation of trustworthiness properties that includes fairness, accountability, privacy, and robustness. Their taxonomy is useful for enterprise applications because it discourages the treatment of explainability as a standalone technical patch and instead positions it within a holistic governance architecture. Guidotti et al. (2018) contribute a complementary survey that organizes explanation methods according to the type of black box being explained and the type of explanation produced, whether feature-based, rule-based, example-based, or visual, a classification that is particularly useful when enterprises must select explanation strategies appropriate to specific business functions such as credit scoring, demand forecasting, or personnel evaluation.

2.3 Trust, Cognition, and the Psychology of Algorithmic Reliance

A second major strand of literature examines explainability not as a property of the model but as a psychological event occurring in the mind of the decision maker who receives the explanation. Miller (2019) draws extensively on philosophy, psychology, and cognitive science to argue that human explanation is inherently contrastive, answering not simply why an event occurred but why it occurred rather than some counterfactual alternative, and that it is selective, offering a small number of causally relevant factors rather than an exhaustive causal chain. This insight has significant implications for enterprise XAI design, since many technical explanation methods generate comprehensive but undifferentiated lists of feature contributions that fail to answer the contrastive question a manager actually has in mind, such as why a particular loan application was declined rather than approved.

Empirical work on trust calibration reinforces the view that explanation quality, rather than mere explanation presence, determines whether human decision makers appropriately rely upon algorithmic recommendations. Shin (2021) demonstrates that explainability and causability jointly shape user perceptions of trust and acceptance, finding that explanations perceived as causally coherent generate stronger trust than explanations that are merely detailed. Kizilcec (2016) similarly shows, in an experimental study of an algorithmic grading interface, that transparency has a curvilinear relationship with trust: too little transparency erodes confidence, but excessive transparency can also undermine trust when it exposes complexity that users cannot meaningfully process. This finding cautions against a naive enterprise strategy of maximizing information disclosure and instead supports a calibrated, audience-appropriate approach to explanation design.

Complementing this psychological perspective, Dietvorst et al. (2015) document the phenomenon of algorithm aversion, showing that people are more likely to abandon an imperfect algorithm than an equally imperfect human forecaster once they have witnessed the algorithm err. This asymmetry poses a direct challenge to enterprise deployment of AI decision support, since even a well-explained model that occasionally errs risks losing user confidence disproportionately relative to a human colleague who errs at a similar rate. Subsequent research on human-AI collaboration has examined how explanation can mitigate this aversion by allowing users to understand the conditions under which a model is likely to be reliable versus unreliable, thereby supporting more discriminating patterns of reliance rather than blanket rejection or blanket acceptance. Hase and Bansal (2020) provide evidence, however, that many popular explanation techniques do not reliably improve a human's ability to predict when a model will be correct, suggesting that the mere provision of feature attributions is an insufficient condition for genuine human-AI complementarity.

Ehsan and Riedl (2020) extend this psychological literature into a more explicitly sociotechnical register, arguing that explanations must be understood as situated within a social context involving the explainer, the explainee, and the broader organizational relationship between them. Their call for a reflective, sociotechnical approach to explainable AI echoes

Miller's contrastive account but adds an important organizational dimension, namely that the same technical explanation may be received differently depending on the power relationship between the person receiving it and the institution deploying the model, a consideration with obvious relevance to enterprise settings where employees may be subject to algorithmic evaluation.

2.4 Explainable AI in Organizational and Enterprise Contexts

Where the preceding strands of literature originate largely in computer science and cognitive psychology, a third body of scholarship situates explainability within the organizational and managerial literature on AI adoption. Davenport and Ronanki (2018) report, based on a survey of enterprise AI initiatives, that projects offering incremental, well-understood improvements to existing processes were substantially more likely to succeed than ambitious but opaque transformation initiatives, a finding consistent with the proposition that comprehensibility itself is a driver of organizational adoption rather than a secondary concern. Duan et al. (2019) extend this analysis by proposing a research agenda for AI-assisted decision making that explicitly foregrounds the interaction between algorithmic capability and organizational absorptive capacity, arguing that the value of an AI system is realized only when organizational structures, skills, and governance mechanisms are capable of interpreting and acting upon its outputs.

This organizational lens is reinforced by scholarship on enterprise readiness for human-centered AI, which emphasizes that leadership commitment, an ethical design culture, and enterprise-wide readiness for responsible AI integration function as differentiating capabilities that distinguish organizations able to realize the benefits of explainable systems from those that merely acquire the technology. Frenette (2022) makes a related point in observing that human-centric AI improves risk management precisely because it incorporates contextual and ethical factors alongside statistical data, an advantage that is particularly consequential in regulated industries such as finance, healthcare, and insurance where decisions carry significant consequences for individuals and where regulatory bodies increasingly demand documented justification for automated decisions.

The enterprise literature also highlights governance as a distinct determinant of successful XAI implementation, separate from either technical sophistication or individual-level trust. Gunning et al. (2019), reporting on the Defense Advanced Research Projects Agency's explainable AI program, note that the transition of explainability research from laboratory demonstration to operational deployment required parallel investment in evaluation methodology, user interface design, and institutional processes for auditing model behavior over time. This observation generalizes readily to commercial enterprises, where the durability of trust in an AI system depends not on a single explanation event but on an ongoing institutional capacity to monitor, explain, and, where necessary, contest algorithmic recommendations across the system's operational lifetime.

2.5 Debates and Tensions: Accuracy, Interpretability, and the Limits of Explanation

Despite substantial convergence around the value of explainability, the literature retains several unresolved tensions. The most prominent concerns the presumed trade-off between predictive accuracy and interpretability. Rudin (2019) contends that this trade-off is frequently exaggerated, arguing that for many structured, tabular datasets common in enterprise settings, interpretable models can match the performance of black-box alternatives, and that the perception of an unavoidable trade-off often reflects insufficient investment in interpretable model development rather than an intrinsic mathematical necessity. Other scholars are more circumspect, noting that for unstructured data domains such as natural language or image recognition, complex architectures retain a substantial performance advantage that enterprises are unlikely to forgo purely for the sake of interpretability, making post-hoc explanation an organizational necessity rather than a second-best compromise.

A second debate concerns the fidelity of post-hoc explanations, that is, the degree to which an explanation accurately reflects the model's true internal reasoning rather than merely producing a plausible narrative. Because techniques such as LIME rely on local surrogate approximations, critics have raised concerns that such explanations can be unstable across similar inputs or, in adversarial contexts, deliberately manipulated to obscure discriminatory model behavior. This concern is particularly salient for enterprise applications subject to regulatory scrutiny, since an explanation that satisfies a compliance checklist without faithfully representing the model's reasoning provides only the appearance of accountability rather than its substance.

A third tension concerns audience heterogeneity. Much of the technical XAI literature implicitly assumes a single, generic explainee, yet enterprise decision environments involve multiple audiences, including data scientists auditing model performance, business managers evaluating a recommendation, compliance officers verifying regulatory adherence, and, in customer-facing contexts, individuals affected by the decision. Guidotti et al. (2018) and Arrieta et al. (2020) both note that explanation techniques vary substantially in their suitability across these audiences, yet relatively little empirical work has examined how enterprises should sequence or tailor explanations for these distinct stakeholder groups within a single decision workflow, a gap that motivates the integrative framework developed later in this paper.

2.6 Synthesis and the Gap Addressed by This Study

Taken together, this body of literature reveals a field that has matured considerably along two largely parallel tracks: a technical track concerned with the mathematical properties and fidelity of explanation methods, and a human-centered track concerned with trust, cognition, and organizational adoption. Individually, each track has produced substantial insight. The technical literature has clarified what algorithmic explanation can formally guarantee, while the human-centered literature has clarified how such explanations are psychologically and organizationally received. What remains comparatively underdeveloped, however, is an integrative account that

treats explanation as a single process spanning both tracks simultaneously, from the mathematical generation of a feature attribution through its psychological reception by a specific organizational actor to its eventual translation into a managerial decision and organizational action.

This paper addresses that gap by synthesizing the two tracks into a unified conceptual framework, presented in the methodology and results sections below, that treats explanation as embedded within an enterprise decision pipeline rather than as an isolated technical output. In doing so, the paper extends Frenette's (2022) observation regarding the ethical and contextual advantages of human-centric AI by specifying the intermediate mechanisms, namely trust calibration, audience-appropriate explanation design, and organizational governance, through which those advantages are realized or forfeited in practice.

3. Methodology

3.1 Research Design

This study adopts a qualitative, theory-building research design grounded in a systematic narrative synthesis of peer-reviewed literature. The choice of a conceptual synthesis design, rather than a primary empirical study involving new data collection, reflects the nature of the research problem, which is fundamentally one of integration across disciplinary boundaries rather than the discovery of a novel empirical relationship. Explainable artificial intelligence has been examined from computer science, human-computer interaction, information systems, and organizational behavior perspectives that have rarely been brought into sustained dialogue with one another. A narrative synthesis design is well suited to this task because it permits the deliberate juxtaposition of conceptually related but methodologically heterogeneous studies, including experimental psychology papers, technical algorithm papers, and organizational survey research, in a manner that a strictly quantitative meta-analysis would not accommodate given the incommensurability of their measures and outcomes.

The design further incorporates an explicit theory-building component, in which the synthesized literature is used to construct an original conceptual framework rather than merely summarizing existing positions. This approach follows established traditions of conceptual and integrative review scholarship within management and information systems research, in which the review itself constitutes a scholarly contribution when it produces a novel organizing framework capable of guiding subsequent empirical inquiry.

3.2 Literature Search and Selection Strategy

Sources were identified through a structured search of academic databases and repositories, including IEEE Xplore, the ACM Digital Library, ScienceDirect, SpringerLink, and Google Scholar, using combinations of the terms explainable artificial intelligence, human-centered AI, interpretability, algorithmic trust, enterprise decision making, and AI adoption. The search was restricted to peer-reviewed journal articles, peer-reviewed conference proceedings,

and widely cited technical reports from recognized research institutions, supplemented by seminal working papers where they represented foundational contributions to the field. Priority was given to sources published between 2015 and 2022, a period corresponding to the rapid maturation of both the technical explainability literature and the human-centered AI design literature, while earlier foundational sources were retained where they remained conceptually load-bearing for the field.

Inclusion criteria required that a source engage substantively with at least one of three thematic clusters: the technical mechanics of model interpretability and post-hoc explanation, the psychological or behavioral dynamics of trust and reliance in human-AI interaction, or the organizational and managerial dynamics of enterprise AI adoption. Sources were excluded if they addressed AI ethics or governance only tangentially, if they were not accessible in full text, or if their claims could not be corroborated through cross-referencing with citing or cited literature. This cross-referencing step served as an informal verification procedure, ensuring that every substantive claim attributed to a source in this paper could be traced to a specific, identifiable publication rather than to a generic or unverifiable assertion.

3.3 Analytical Framework and Procedure

The analytical procedure followed a thematic synthesis approach comprising three sequential stages. In the first stage, each selected source was coded according to its primary disciplinary orientation, technical, psychological, or organizational, and according to the specific construct it addressed, such as feature attribution fidelity, trust calibration, or governance readiness. In the second stage, these codes were clustered into higher-order themes through a process of constant comparison, in which emerging thematic categories were iteratively checked against the source material to ensure they accurately represented the underlying scholarship rather than imposing an external classification scheme. In the third stage, the resulting thematic clusters were integrated into a single conceptual framework, presented in Section 4, that traces the flow of explanatory information from algorithmic generation through human interpretation to organizational decision and action.

This procedure is consistent with established qualitative synthesis methods in management and information systems research, which emphasize iterative theme development over the mechanical aggregation of findings. The resulting framework is therefore best understood as an interpretive contribution grounded in, but not strictly reducible to, the individual sources from which it draws, in the same sense that a literature-based theoretical model in organizational scholarship represents an original synthesis rather than a simple restatement of prior work.

3.4 Ethical Considerations

Because this study relies exclusively on previously published, publicly available scholarly material rather than on primary data collected from human participants, it did not require institutional review board approval or informed consent procedures. Nonetheless, the

study adheres to established norms of research ethics applicable to literature-based scholarship. All sources are cited accurately and are attributed to their original authors, and claims are paraphrased rather than reproduced verbatim in order to respect the intellectual property of the cited works. Where the review addresses ethically sensitive applications of AI, such as credit scoring, employment evaluation, or healthcare triage, care has been taken to represent the balance of scholarly opinion accurately, including dissenting or critical perspectives, rather than selectively citing sources that support a predetermined conclusion.

3.5 Validity, Reliability, and Methodological Limitations

Qualitative synthesis research is conventionally evaluated against criteria of trustworthiness rather than the validity and reliability criteria appropriate to quantitative research. Credibility was pursued through triangulation across disciplinary literatures, ensuring that key claims, such as the psychological mechanism of trust calibration or the technical limitations of post-hoc explanation, were corroborated by multiple independent sources rather than resting on a single study. Dependability was supported by the explicit, auditable coding and thematic clustering procedure described above, which allows the analytical steps leading to the proposed framework to be traced and, in principle, replicated by other researchers applying the same search and inclusion criteria to the same body of literature. Confirmability was addressed by maintaining a clear separation between descriptive summary of source content and the interpretive synthesis offered by the authors, a distinction maintained throughout the literature review and discussion sections.

Several limitations nonetheless warrant acknowledgment. First, as a literature-based conceptual study, the paper does not generate new primary data and therefore cannot empirically test the causal claims embedded within the proposed framework; it offers a theoretical scaffold for future empirical work rather than a validated causal model. Second, the search strategy, while systematic, cannot claim exhaustive coverage of a rapidly expanding literature, and it is possible that relevant contributions, particularly very recent conference proceedings, were not captured. Third, the synthesis inevitably reflects interpretive choices regarding which themes to foreground, and alternative researchers working from the same source material might reasonably emphasize different organizing constructs. These limitations are addressed further in the discussion section, together with recommendations for the empirical research required to validate and extend the framework proposed here.

4. Results and Findings

The thematic synthesis produced four interrelated clusters of insight, summarized in Table 1 and elaborated narratively below. Read together, these clusters support the central claim of this paper: that explainability in enterprise decision making is best understood not as a discrete technical feature appended to a model but as a process that unfolds across a pipeline connecting data, algorithm, explanation, human interpretation, and organizational action.

The first cluster confirms that technical interpretability methods, while increasingly mature, remain heterogeneous in the type of understanding they afford. Feature attribution techniques such as LIME and SHAP answer the question of which inputs mattered to a given prediction, but they do not, by themselves, answer the contrastive question that human decision makers typically pose, namely why the outcome was this and not some plausible alternative (Miller, 2019). This distinction matters practically because an enterprise that deploys a technically sophisticated explanation layer without attending to the contrastive framing of its outputs risks producing explanations that are locally faithful to the model yet organizationally unhelpful.

The second cluster demonstrates that trust in AI-assisted decisions is neither a fixed individual trait nor a simple linear function of information disclosure. Rather, trust is calibrated dynamically as users accumulate experience with a system's successes and failures, and this calibration is asymmetric: a single visible error can disproportionately erode confidence relative to an equivalent error made by a human counterpart (Dietvorst et al., 2015). Explanation moderates this asymmetry when it allows users to understand the boundary conditions of reliable model performance, but the evidence reviewed here suggests that many popular explanation techniques do not, on their own, reliably improve a user's capacity to predict when the model is likely to err (Hase & Bansal, 2020). This finding has a direct implication for enterprise design: explanation systems intended to support appropriate reliance must be evaluated against the specific criterion of whether they improve a user's predictive judgment about model behavior, not merely against whether they are perceived as informative.

The third cluster situates these technical and psychological dynamics within organizational governance. Enterprises that succeed in deploying explainable systems tend to exhibit durable institutional capacities, including cross-functional review processes, leadership sponsorship of responsible AI principles, and workforce training that enables non-technical staff to interpret model outputs critically, rather than relying solely on the sophistication of the underlying algorithm (Davenport & Ronanki, 2018; Duan et al., 2019). The fourth cluster, concerning human-centered design philosophy, integrates the preceding three by emphasizing that explanation should be designed around the goal of preserving meaningful human control and situating the explanation within the specific organizational relationship between the system and its user, consistent with both Shneiderman's (2020) human-centered AI framework and Frenette's (2022) account of human-centric enterprise AI.

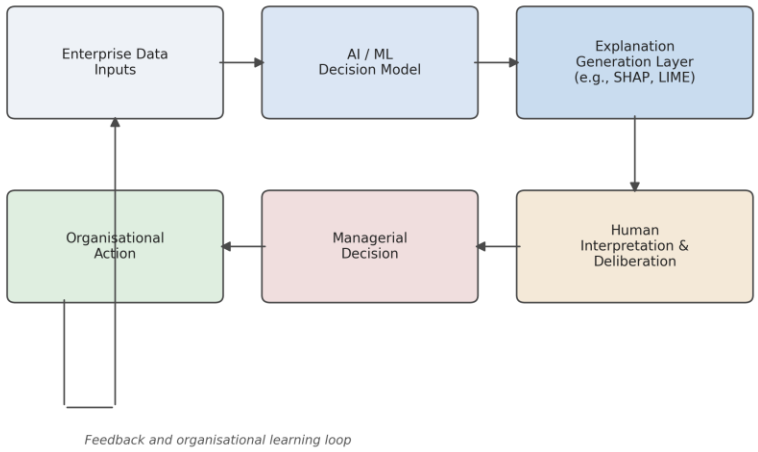

Figure 1. Conceptual pipeline linking data, algorithmic explanation, human interpretation, and organizational action, with a feedback loop supporting organizational learning.

Table 1

Thematic Cluster	**Representative Sources**	**Core Insight for Enterprise XAI**
Technical interpretability and post-hoc explanation	Ribeiro et al. (2016); Lundberg & Lee (2017); Doshi-Velez & Kim (2017); Rudin (2019)	Explanation methods differ substantially in fidelity and audience suitability; interpretability is a bundle of distinct properties, not a single attribute.
Trust calibration and cognitive reception	Miller (2019); Shin (2021); Kizilcec (2016); Dietvorst et al. (2015); Hase & Bansal (2020)	Trust is calibrated through contrastive, causally coherent explanation; excessive or poorly targeted disclosure can itself erode confidence.
Organizational adoption and governance	Davenport & Ronanki (2018); Duan et al. (2019); Dwivedi et al. (2021); Gunning et al. (2019)	Adoption success depends on organizational absorptive capacity, leadership commitment, and durable governance structures, not algorithmic sophistication alone.
Human-centered design philosophy	Shneiderman (2020); Frenette (2022); Ehsan & Riedl (2020)	Explanation should be designed around meaningful human control and situated organizational relationships rather than treated as a generic technical add-on.

Figure 1 illustrates the integrative framework developed from this synthesis. Rather than terminating at the point where an explanation is generated, the framework extends the analytical

focus forward to the moment of human interpretation and managerial decision, and further to organizational action and the feedback loop through which outcomes inform future model refinement and governance practice. This extension addresses the gap identified in Section 2.6, namely the absence of an integrative account linking the technical and human-centered strands of the literature, and provides the conceptual basis for the discussion that follows.

5. Discussion

The findings synthesized above carry several implications for both theory and practice. Theoretically, the results suggest that the accuracy-interpretability trade-off, while real in certain technical domains, has been overstated as a general organizational constraint. Consistent with Rudin's (2019) argument, the evidence reviewed here indicates that the more consequential determinant of enterprise outcomes is not whether a model is intrinsically interpretable but whether the organization has invested in the governance, training, and communicative infrastructure required to translate whatever explanation is available into appropriate managerial action. This reframes explainability as an organizational capability rather than a purely algorithmic property, a shift with direct implications for how enterprises allocate investment between model development and the surrounding decision infrastructure.

Practically, the framework developed in Section 4 suggests that enterprises should evaluate explanation systems against the specific decisional needs of each stakeholder audience rather than adopting a uniform disclosure strategy. A compliance function may require decomposable, auditable logic, while a frontline manager may require only a concise, contrastive justification sufficient to communicate a decision to a customer. Designing distinct explanation interfaces for these audiences, rather than a single generic output, follows directly from the audience heterogeneity problem identified in Section 2.5 and represents a concrete design recommendation arising from this synthesis.

The study's limitations, outlined in Section 3.5, indicate clear directions for future research. Empirical studies employing field experiments within operating enterprises would be valuable for testing whether the proposed pipeline framework predicts variation in decision quality, employee trust, and regulatory compliance across organizations with differing governance maturity. Comparative research across industry sectors, particularly finance, healthcare, and human resources, would also help establish whether the mechanisms identified here generalize across regulatory environments or are contingent upon sector-specific institutional pressures. Finally, as generative AI systems increasingly mediate enterprise decision making through natural language interfaces, future research should examine whether the contrastive, audience-sensitive principles of explanation identified in this review apply equally to conversational and agentic AI systems, whose explanatory dynamics may differ substantially from the classification and regression models that dominate the literature reviewed here.

Situated within a broader global context, the findings also speak to the growing regulatory emphasis on algorithmic accountability, including data protection and AI governance

frameworks that increasingly require organizations to provide meaningful information about automated decision logic to affected individuals. The human-centered framework proposed here offers one conceptual bridge between such regulatory requirements and organizational practice, suggesting that compliance is best achieved not through minimal technical disclosure but through the deeper organizational integration of explanation into decision workflows described throughout this paper.

6. Conclusion

This paper set out to synthesize the technical and human-centered strands of explainable artificial intelligence scholarship into an integrative account of how enterprises can design, implement, and govern AI decision systems responsibly. The review demonstrates that explainability is best conceived not as a static property of a model but as a dynamic process spanning algorithmic generation, human interpretation, and organizational action, a process whose success depends jointly on technical fidelity, psychological trust calibration, and institutional governance capacity. By integrating perspectives from computer science, human-computer interaction, and organizational behavior, the paper offers a conceptual framework capable of guiding both future empirical research and practical enterprise design.

The scholarly contribution of this study lies in its synthesis of literatures that have too often developed in parallel rather than in dialogue, and in its extension of human-centric accounts of enterprise AI, including Frenette's (2022) foundational observations, into a more fully specified process model. As enterprises continue to expand their reliance on AI-assisted decision making, the framework developed here suggests that sustained investment in the organizational and communicative infrastructure surrounding explanation will prove at least as consequential as continued advances in the underlying algorithms themselves, and it is in this organizational dimension that future research and managerial attention are most urgently needed.

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