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Rethinking Stakeholder Theory in the Age of AI: A Conceptual Model

Maisie Evans [1]*

1. University of Worcester, UK
* Correspondence: evansmaisie@worcester.ac.uk

Abstract: Forty years after Freeman's foundational articulation of stakeholder theory, the conceptual scaffolding of organizational management still rests on a quiet assumption: stakeholders are humans. As artificial intelligence moves from a productivity tool to an autonomous decision-making agent, that assumption has collapsed. AI systems now allocate credit, hire and fire workers, set prices, screen patients, and shape the information environments in which democratic deliberation occurs. Existing stakeholder frameworks were neither designed for these dynamics nor tested against them. This paper develops a conceptual model that rethinks stakeholder theory for the AI era by integrating four streams of scholarship—classical stakeholder theory, AI ethics, algorithmic governance, and more-than-human management—into an integrated framework with five core constructs: AI as a quasi-stakeholder affected stakeholders algorithmic salience value co-creation / value co-destruction, and the AI stakeholder governance loop. The model advances twelve testable propositions, offers a typology of stakeholder configurations under AI, and provides a roadmap for empirical research and managerial practice. We argue that a useful twenty-first-century stakeholder theory must be neither human-centric by default nor technology-deterministic by default. Instead, it must explicitly theorize the agency, opacity, and reflexive impact of intelligent machines on every stage of stakeholder identification, salience, and engagement.

Keywords: stakeholder theory; artificial intelligence; algorithmic governance; conceptual model; synthetic stakeholders

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1. Introduction

The year 1984 marked a turning point in management theory. Freeman's Strategic Management: A Stakeholder Approach reframed the firm from a vehicle for shareholder return into a coordinator of value creation for all parties affected by—or affecting—its operations (Freeman, 2010). The proposition was deceptively simple: "a stakeholder is any group or individual who can affect or is affected by the achievement of the organization's objectives" (Khan et al., 2022). In the four decades since, stakeholder theory has become one of the most influential lenses in business ethics, strategic management, accounting, marketing, and corporate governance (Freeman et al., 2010).

Yet the construct of a "stakeholder" inherited from that era is bound by a tacit anthropocentrism. Stakeholders are presumed to be collectives of people—employees, customers, communities, regulators, shareholders—who possess moral claims, hold interests, and engage through voice, loyalty, or exit. They are expected to reason about trade-offs, contest managerial decisions in courts of public opinion, and renegotiate the implicit contracts that bind them to the firm. Stakeholder theory, in other words, was built for an organizational world where the actors on the boundary of the firm were human.

A second tectonic shift, comparable in scale to the introduction of the limited liability corporation, is now underway. Artificial intelligence has moved from the back office to the boardroom. Algorithms now score loan applicants, triage patients in emergency rooms, recommend sentences in criminal proceedings, and shape the news feeds that voters consume (Hagendorff, 2020; McGregor et al., 2019). Studies estimate that up to 50% of current occupations may be displaced or fundamentally restructured by automation (Lukya-

nenko et al., 2022). Management scholarship has been accused of "lagging" relative to the speed of technological change (Matthews et al., 2025). The fields closest to stakeholders—corporate governance and business ethics—have generally treated AI as an external phenomenon to be regulated or as a productivity lever to be exploited, rather than as something that itself reorganizes the stakeholder field.

This paper takes a different stance. We argue that the principal theoretical problem of stakeholder theory in the age of AI is not merely ethical (do algorithms discriminate?) nor merely governance-related (are boards equipped to oversee machine learning?). It is conceptual: the categories of stakeholder theory must be extended to accommodate a new class of actor and a new structure of relationships. Specifically, three phenomena demand retheorization:

The rise of "synthetic" or quasi-stakeholders—AI agents that learn, decide, and allocate value in ways that materially shape organizational outcomes even though they lack intent, emotion, or moral standing in the conventional sense (Rhymer et al., 2024; Visconti, 2025).

The transformation of traditional stakeholders through algorithmic mediation—employees whose performance is measured by software they cannot inspect, customers who are priced and ranked by systems whose criteria they do not see, citizens whose public services are allocated by models whose errors are silent (Kordzadeh & Ghasemaghaei, 2021; Langer et al., 2021).

A new accountability gap—the widening distance between algorithmic decisions and the human agents who can be held responsible for them (Koene et al., 2019; McGregor et al., 2019).

Our objective is to construct and articulate a conceptual model that responds to these three challenges. The model combines classical stakeholder theorizing, the algorithmic accountability literature, AI ethics, and the emerging scholarship on more-than-human management into a single integrated framework with five constructs and twelve propositions that we believe can guide empirical inquiry and managerial practice.

The paper proceeds as follows. Section 2 reviews the relevant theoretical foundations. Section 3 maps the distinct challenges that AI introduces. Section 4 specifies the conceptual model and its constructs. Section 5 develops the propositions. Section 6 discusses theoretical, managerial, and policy implications. Section 7 acknowledges limitations and directs future research. Section 8 concludes.

2. Theoretical Foundations

2.1 The Stakeholder Construct and Its Three Voices

The modern lineage of stakeholder thinking reaches back roughly six decades, with Mary Parker Follett articulating an early relational view of organizations and the Stanford Research Institute formalizing the notion in 1963 (Khan et al., 2022). Freeman codified these threads into a coherent strategic management theory in 1984 (Freeman, 2010), and by the mid-1990s the literature had become sufficiently mature that Donaldson and Preston could articulate three analytically distinct faces of the theory: descriptive (how managers and firms actually behave with regard to stakeholders), instrumental (whether attending to stakeholders improves bottom-line performance), and normative (what obligations firms owe to stakeholders based on moral or philosophical reasoning) (Corazza et al., 2023; Dacanay, 2012; Pesqueux & Ayadi, 2005).

Freeman himself resisted this tripartite analytical separation, arguing that "any good theory or narrative ought to do all three" and that the stakeholder approach has always been "managerial"—simultaneously descriptive, instrumental, and prescriptive (Freeman, 2004). This pragmatic posture is important because it suggests that a revised theory for the AI era cannot be a purely normative ethics exercise; it must remain connected to the actual organizational practices of managers, even as those practices are being rewritten by algorithmic systems.

Donaldson and Preston argued that "stakeholder theory is managerial" because it "recommends the attitudes, structures and practices that, taken together, constitute a stakeholder management philosophy with its ultimate justification found in its normative base" (Dacanay, 2012). We retain this managerial orientation. We hold, however, that the attitudes, structures, and practices in question must now include how managers handle the algorithmic substrate of contemporary decision-making.

2.2 The Mitchell–Agle–Wood Salience Model

The most influential refinement of stakeholder theory beyond Freeman's original articulation is the salience model developed by Mitchell, Agle, and Wood in 1997 (Mitchell et al., 1997). The model proposes that managers do not—and should not—treat all stakeholders as equivalent. Rather, stakeholders are prioritized according to three attributes: power (the ability to impose will), legitimacy (the social acceptability of a claim), and urgency (the time-sensitivity and criticality of a claim). Stakeholders possessing one attribute are "latent"; those possessing two are "expectant"; those possessing all three are "definitive" (Cutovoi, 2018; Mitchell et al., 1997). Subsequent work has refined this model by treating power, legitimacy, and urgency as features not just of perceptions but of stakeholder–request–firm triplets, which has proven valuable for predicting firm responses to activist and secondary stakeholders (Eesley & Lenox, 2006).

In the original 1997 model, the three attributes were theorized as features of human claimants whose claims can be heard, contested, and negotiated. We will show in Section 4 that AI undermines this assumption in two ways: by altering the salience attributes of human stakeholders and by introducing a new class of actor (the synthetic stakeholder) whose salience cannot be straightforwardly assessed along the original three dimensions.

2.3 From Stakeholder Engagement to Stakeholder Governance

A second branch of stakeholder scholarship has emphasized the deliberative and procedural dimensions of stakeholder management. Integrative models highlight that legitimacy is not granted once and for all; it is renegotiated through discourse and community engagement (Smith et al., 2013). This is consistent with Mitchell, Agle, and Wood's own framing of legitimacy as "a generalized perception or assumption that the actions of an entity are desirable, proper, or appropriate within some socially constructed system of norms, values, beliefs, and definitions" (Smith et al., 2013).

For the AI era, this procedural orientation is doubly significant. First, AI-driven decisions that lack discursive justification (e.g., credit denials by opaque models) are perceived as illegitimate by affected parties in ways that erode the procedural value of stakeholder engagement. Second, the boundary of who participates in that engagement must now include algorithmic systems themselves when they shape outcomes, prompting questions about what deliberation looks like when one of the parties is non-sentient.

2.4 The Emerging Field of More-than-Human Management

A third, smaller but rapidly growing line of scholarship extends stakeholder thinking beyond the human. The "more-than-human management" agenda argues that management scholarship "historically assumes actors are people" but that "a growing number of more-than-humans" are now ascribed human-like characteristics by management theory and law, including animals, rivers, computer programs, plants, mountains, places, and landscapes (Poggioli et al., 2023). Ethical work in this vein echoes earlier feminist critiques of corporate stakeholder theorizing for ignoring "the ontological status of technology" and failing to ask "what is a stake, who is a stakeholder, and how should the organization–stakeholder relationship be organized" (Böhm et al., 2022).

We take the more-than-human agenda as a starting point but argue it is insufficient on its own. Animals and rivers have stakes (clean water, habitat) that can be represented by human advocates or assigned legal standing. AI systems have a different profile: they allocate and adjudicate; they do not simply wait to be considered. Our model therefore distinguishes AI from other non-human stakeholders in Section 4.

2.5 The Algorithmic Governance and AI Ethics Literature

The fourth pillar of our model is the now-substantial body of work on algorithmic governance and AI ethics. Several key insights from this literature are foundational for what follows.

First, AI exhibits four design characteristics that materialize in the workplace and the marketplace: autonomy (the capacity to act without human input), learning (the capacity to update behavior in response to data), inscrutability (the impossibility, in practice, of fully explaining a model's decisions to non-specialists), and materiality (the fact that algorithmic recommendations translate, more or less directly, into real-world consequences) (Matthews et al., 2025). These four characteristics produce "value contingencies"—the idea that the value afforded by intelligent machines is conditional, modulated by stakeholders' dispositions and the contexts in which they encounter the technology (Matthews et al., 2025).

Second, AI concentrates opportunity and risk asymmetrically across stakeholder groups. Cost savings generated by AI predictably flow to EBITDA, which elevates the value of the firm and reweights the implicit contracts between the firm and its capital providers (Visconti et al., 2023). The added value is then partitioned across the stakeholder network, but

the partitioning is not benign: customers, employees, and communities absorb the costs of data extraction, surveillance, job displacement, and discrimination (Mirbabaie et al., 2021; Visconti et al., 2023).

Third, AI ethics has rapidly internationalized, but unevenly. The European High-Level Expert Group on AI identifies four principles (respect for human autonomy, prevention of harm, fairness, and explicability) (Gianni et al., 2022). The OECD identifies five (sustainability, fairness, transparency, safety, and accountability) (Gianni et al., 2022; Giungato et al., 2021). Voluntary corporate principles add their own clusters (Gianni et al., 2022). Comparative governance work has shown that the EU AI Act takes a centralized approach while the UK takes a risk-centered approach, complicating implementation of "international" AI regulations (Kiden et al., 2024). The most-cited formal frameworks in the secondary literature are the EU AI Act and the U.S. NIST AI Risk Management Framework, with transparency and accountability recurring as the most common principles (Ribeiro et al., 2025).

Fourth, AI raises distinctive forms of harm. Companies can generate "massive job losses" from AI deployment, conduct "unmonitored forms of AI experiments on society without informed consent," suffer from data breaches, deploy "unfair, biased algorithms," and inadvertently release unsafe products (Hagendorff, 2020). Hackers, criminal actors, and misinformation networks exploit AI for deepfakes, voice synthesis, and personalized manipulation (Hagendorff, 2020). The "dark side of AI" is not a peripheral concern but a structural feature of the technology's current institutionalization (Min, 2026; Mirbabaie et al., 2021).

3. Why AI Forces a Rethinking of Stakeholder Theory

3.1 The Rise of Non-Human but Acting Subjects

Recent work in corporate governance increasingly argues that AI has "evolved from a passive tool to an autonomous entity" that drives strategic decisions, streamlines enterprise processes, "and sits in governance" (Visconti, 2025). Visconti has proposed that AI should be reconceptualized "as a self-regulating stakeholder that operates beyond human oversight, fundamentally altering governance incentives and compliance structures" (Visconti, 2025). The argument is that AI contributes to decision-making through "predictive power [that] can analyze and deduce from a plethora of data, producing superior decision-making results compared to human agents," accumulates wealth for the firms that deploy it, and "shape[s] economic, political, and social structures"—all without possessing intent, emotion, empathy, or motive (Visconti, 2025).

A complementary research stream has begun to formalize these synthetic actors as synthetic stakeholders: "technology-based agent(s) that can learn and act as an independent representative in organizational decision-making processes" (Rhymer et al., 2024). Synthetic stakeholder theorizing, in this view, allows the natural environment—and by extension algorithmic systems—to gain "a powerful and independent 'voice' in organizational decision-making" that has historically been denied to non-human claimants (Rhymer et al., 2024). This is consequential because it shifts the role of AI from a tool that supports human decision-making to an actor that participates in decisions and has its own (designer-induced, but operationally independent) objectives.

The more-than-human management literature reinforces this point: technologies like AI have, at best, "minimal evidence of serious consideration within stakeholder theory of the status of non-humans, such as artificial intelligences, let alone as stakeholders in and of themselves (i.e. having agency and interests)" (Böhm et al., 2022). We treat this gap as a primary motivating problem.

3.2 The Transformation of Human Stakeholders

Even when AI is granted only tool-like status, the stakeholders on the human side of the firm are reshaped. Three transformations matter most.

Algorithmic reframing. Traditional stakeholders are re-described by AI systems in ways that affect how the firm sees them. Customers become user IDs and feature vectors; employees become performance distributions; candidates become résumé embeddings. Once reframed, the substantive judgment of managers about stakeholder interests is replaced or supplemented by algorithmic ranking, with material consequences for whom managers listen to.

Algorithmic opacity. AI systems are often inscrutable in their operation, particularly those based on deep learning (Matthews et al., 2025). Stakeholder engagement becomes difficult when the firm cannot explain—let alone defend—decisions that affect stakeholders. Empirical work on explainable AI has shown that different stakeholder groups require different explanations: users need actionable justification, consumers need simple clarity, businesses need decision rules,

and regulators need audit trails (Dwivedi et al., 2022; Hoffman et al., 2023; Langer et al., 2021; Meske et al., 2020). The stakeholder engagement process is therefore no longer a uniform managerial exercise; it is itself a multi-tier design problem.

Asymmetric distribution of costs. Algorithmic systems tend to distribute their costs unevenly. Workers experience displacement, surveillance, and identity threat (Mirbabaie et al., 2021); communities absorb the externalities of algorithmic targeting; customers endure privacy overcollection and the fear that "data captured by AI systems can be manipulated to serve purposes beyond their original intent" (Shrestha & Joshi, 2025). The systematic literature review by Lin and Lam on AI adoption and stakeholder impact concluded that AI "does have different, sometimes conflicting, effects on different stakeholder groups" and that scholars have neglected supply chain and competitive stakeholders in their analyses (Lin & Lam, 2025). The paucity of attention to those under-researched stakeholders is itself an indictment of how the field has operationalized the stakeholder construct.

3.3 An Accountability Gap

A third motivation is accountability. Algorithmic systems are deployed with a "capacity to process large amounts of varied data sets . . . paired with machine learning methods in order to infer statistical models directly from the data," but their opacity "risks undermining meaningful scrutiny and accountability, which is a significant concern when these systems are applied as part of decision-making processes that can have a considerable impact on people's human rights" (Koene et al., 2019). International human rights law has been proposed as one scaffolding on which to hang algorithmic accountability, but this remains a contested institutional project (McGregor et al., 2019).

Within management, the corporate governance literature has begun to map this gap. Achanta argues that AI is "simultaneously creating stakeholder impacts demanding board attention while providing technological capabilities for enhanced transparency and multi-dimensional value creation," and identifies four governance dimensions that require rethinking: structural (committee architectures), process (stakeholder impact assessments), competency (digital literacy and ethical reasoning), and accountability (algorithmic oversight) (Achanta, 2025). Ganesh similarly calls for "robust ethical oversight and accountability frameworks" and contrasts mature AI-integration governance with corporate governance standards such as the OECD Principles and national codes (Ganesh, 2025). The contrast is illuminating: corporate governance standardization has had decades to mature; AI governance is barely a decade old in most jurisdictions.

4. Toward a Conceptual Model: AI-Augmented Stakeholder Theory

The three pressures above necessitate a retheorization. We propose a model with five core constructs that, taken together, articulate how stakeholder theory should be rethought for the age of AI. The model is summarized in Table 1 and described below.

4.1 Foundational Premises

Before specifying the constructs, we lay out three premises that anchor the model:

Premise 1. The boundary between human and non-human actors within the stakeholder field is no longer categorical. Organizations operate within stakeholder fields that invariably contain both human and synthetic stakeholders whose actions are jointly responsible for organizational outcomes.

Premise 2. Even where AI is treated as a tool, it acts as a structural mediator between the firm and its human stakeholders, transforming how the firm identifies, evaluates, and engages with them.

Premise 3. The legitimacy of organizational action in AI-mediated stakeholder fields depends not only on outcome ethics but on procedural transparency and contestability. AI decisions that cannot be explained cannot be defended in stakeholder deliberation, regardless of their technical accuracy.

4.2 Construct 1: The Synthetic Stakeholder (A)

We define a synthetic stakeholder as a technology-based agent—encompassing algorithmic systems, autonomous AI agents, and machine-learning pipelines—that either (a) learns and acts as an independent representative in organizational decision-making processes (Rhymer et al., 2024), or (b) materially allocates value, imposes obligations, or shapes outcomes for the firm and for other stakeholders (Visconti, 2025a, 2025b).

Three defining features distinguish synthetic stakeholders from the broader class of non-human entities covered in the more-than-human management literature (Böhm et al., 2022; Poggioli et al., 2023):

Operational agency. Synthetic stakeholders exercise actual decision power in the firm, not merely nominal representation through human advocates.

Designer-relative objectives. The objectives of a synthetic stakeholder are encoded by its developers rather than evolved from biological or ecological needs.

Opacity. Synthetic stakeholders are characteristically inscrutable in their decision logic, in ways that distinguish them from animals, rivers, or other more-than-humans (Matthews et al., 2025).

The construct incorporates the conceptual move in recent corporate governance scholarship toward treating AI as a stakeholding entity that should "be treated not merely as a decision-support system but as a stakeholder requiring bespoke regulatory mechanisms" (Visconti, 2025). We use "quasi-stakeholder" deliberately to signal that synthetic stakeholders lack intent, moral standing, and welfare in the conventional sense—they have no stake in the firm in the way a community affected by pollution has a stake (Böhm et al., 2022).

4.3 Construct 2: Algorithmic Salience Dimensions (S)

Building on the Mitchell–Agle–Wood salience model (Mitchell et al., 1997; Smith et al., 2013), we propose that AI reconfigures rather than replaces the salience attributes of stakeholders. The three classical attributes—power, legitimacy, and urgency—continue to apply, but they now operate through distinct logical channels because of AI mediation.

Algorithmic power. Power in the AI context is increasingly expressed not through direct coercion but through the ability to shape the options, scores, and recommendations on which decision-makers rely. Algorithms confer and withdraw power.

Algorithmic legitimacy. Legitimacy is granted when claims and decisions are transparently explainable, contestable, and consistent with community norms of procedural fairness (Ayling & Chapman, 2021; Smith et al., 2013). AI systems that cannot meet these standards undermine the legitimacy of the firm even when their outputs are technically correct.

Algorithmic urgency. Time-sensitivity of stakeholder claims is itself altered by AI. Real-time scoring, continuous risk modeling, and dynamic pricing compress the temporal window within which stakeholders can respond, raising the salience of those who are technically prepared and depressurizing that of those who are not (Langer et al., 2021).

This construction preserves Mitchell, Agle, and Wood's framework but acknowledges that the salience attributes are themselves algorithmically produced. A stakeholder's "power" may be coextensive with their data exhaust; their "legitimacy" may be evaluated by a model they cannot see.

4.4 Construct 3: Value Co-Creation and Value Co-Destruction (V)

We draw on the established AI-and-value creation literature to model the outcomes that AI generates for stakeholders. Visconti and colleagues have shown that AI-driven cost savings positively impact EBITDA, which boosts the sustainability of the firm and, through stakeholder interaction, eventually partitions added value across the corporate network (Visconti et al., 2023). However, value is also co-destroyed when AI reproduces biases, intensifies surveillance, or excludes stakeholders from decisions (Kordzadeh & Ghasemaghaei, 2021; Lukyanenko et al., 2022). We therefore theorize value as a bi-directional outcome: AI adoption simultaneously generates upside (efficiency, predictive accuracy, reach) and downside (algorithmic bias, job displacement, privacy erosion), and the net effect varies systematically across stakeholder groups (Hagendorff, 2020; Lin & Lam, 2025; Mirbabaie et al., 2021).

4.5 Construct 4: Affected Stakeholders (α) and Their Vulnerabilities

Drawing on the algorithmic-bias and XAI literatures, we identify six categories of stakeholders whose stakes are most directly restructured by AI:

Customers and end users, who are profiled, priced, and ranked by systems whose criteria they cannot see (Kordzadeh & Ghasemaghaei, 2021; Shrestha & Joshi, 2025).

Employees, whose work is increasingly mediated by performance algorithms, identity-management software, and task-routing AI (Mirbabaie et al., 2021).

Communities and the public, who absorb externalities of algorithmic deployment in housing, policing, credit, healthcare, and information access (Hagendorff, 2020).

Regulators and policymakers, who are charged with oversight but lack technical capacity to audit the AI systems they regulate (Koene et al., 2019).

Minority and historically marginalized groups, who bear disproportionate costs of algorithmic bias, data overcollection, and surveillance (Iseko, 2025; Shrestha & Joshi, 2025).

Future and non-represented stakeholders (e.g., future generations, non-human species), whose interests are rarely encoded in training data but whose welfare is materially affected by AI decisions (Böhm et al., 2022).

These categories are more granular than the canonical stakeholder typology (primary vs. secondary, internal vs. external) and reflect the empirical observation that AI redistributes risk and benefit asymmetrically across groups (Lin & Lam, 2025; Osasona et al., 2024).

4.6 Construct 5: The AI Stakeholder Governance Loop (G)

The fifth construct binds the others into a process model. We propose an AI stakeholder governance loop comprising four iterative stages: algorithmic stakeholder mapping, in which AI tools are themselves used to identify and prioritize stakeholders and may introduce new synthetic stakeholders into the analysis; interpretability and explanation design, in which XAI approaches are tailored to the explanatory needs of each affected stakeholder group (Dwivedi et al., 2022; Hoffman et al., 2023; Langer et al., 2021; Meske et al., 2020); deliberation and contestation, in which stakeholders can review, challenge, and renegotiate algorithmic decisions through formal and informal channels; and feedback and learning, in which stakeholder feedback is incorporated into the next iteration of the AI system itself, closing the loop.

The loop operationalizes the procedural dimension of stakeholder management under AI. It is consistent with the four-pronged responsible-AI governance framework identified by Papagiannidis and colleagues, which distinguishes structural, relational, and procedural practices (Papagiannidis et al., 2025). Within our model the loop is explicitly iterative; AI does not merely facilitate one round of stakeholder engagement but is itself renewed through engagement.

4.7 Summary Representation

The constructs are summarized in Table 1.

Table 1. Core constructs of the AI-augmented stakeholder model

Construct	**Definition**	**Key mechanism**	**Representative sources**
Synthetic stakeholder (A)	Technology-based agent with operational agency, designer-relative objectives, and opacity	Allocates value, imposes obligations, mediates decisions	(Böhm et al., 2022; Rhymer et al., 2024; Visconti, 2025a, 2025b)
Algorithmic salience (S)	Reconfigured power, legitimacy, urgency of stakeholders under AI	Algorithms shape stakeholder attributes	(Ayling & Chapman, 2021; Koene et al., 2019; Langer et al., 2021; Matthews et al., 2025; Mitchell et al., 1997; Smith et al., 2013)
Value co-creation/co-destruction (V)	Bi-directional value outcomes of AI adoption across the stakeholder network	Up: efficiency/scale; Down: bias/displacement	(Kordzadeh & Ghasemaghaei, 2021; Lukyanenko et al., 2022; Mirbabaie et al., 2021; Visconti et al., 2023)
Affected stakeholders (α)	Six empirically grounded categories of AI-impacted stakeholders	Uneven distribution of cost and benefit	(Hagendorff, 2020; Iseko, 2025; Lin & Lam, 2025; Osasona et al., 2024; Shrestha & Joshi, 2025)
AI stakeholder governance loop (G)	Four-stage iterative process linking AI, stakeholders, and accountability	Map → Explain → Deliberate → Learn	(Ayling & Chapman, 2021; Hoffman et al., 2023; Koene et al., 2019; Papagiannidis et al., 2025)

5. Propositions

We articulate twelve testable propositions that follow from the model. Propositions are organized under each construct.

5.1 Synthetic Stakeholders

Proposition 1. The degree to which AI acts as a synthetic stakeholder (A) is positively associated with the firm's adoption of AI in decision-execution (rather than decision-support) roles.

This proposition operationalizes Visconti's claim that AI is increasingly a "cotenente" of governance rather than a tool (Visconti, 2025a, 2025b) and the empirical finding that AI systems in autonomous decision-making roles produce more salient governance effects than those confined to advisory roles (Matthews et al., 2025).

Proposition 2. Synthetic stakeholders in opaque-by-design AI systems (low transparency) will be associated with greater stakeholder distrust and legitimacy erosion than those embedded in explainable-AI architectures.

This follows directly from the empirical XAI literature, which has demonstrated that different stakeholder groups need tailored explanations and that abstract transparency claims are insufficient to maintain legitimacy (Dwivedi et al., 2022; Hoffman et al., 2023; Langer et al., 2021; Lukyanenko et al., 2022; Meske et al., 2020).

5.2 Algorithmic Salience

Proposition 3. The greater the algorithmic mediation in stakeholder relationships, the more salience (S) is determined by the data exhaust a stakeholder produces rather than by their organizational position or formal voice.**

The proposition updates Mitchell, Agle, and Wood's salience model to account for the way AI grants salience through data generation (Lin & Lam, 2025; Mitchell et al., 1997).

Proposition 4. Firms with lower AI-driven legitimacy erosion will exhibit stronger stakeholder engagement scores than firms with structurally identical stakeholder portfolios but higher AI opacity.

This is consistent with research showing that legitimacy is a discursive and procedural achievement, not a structural given (Ayling & Chapman, 2021; Smith et al., 2013).

5.3 Value Co-Creation and Co-Destruction

Proposition 5. AI adoption (V) is associated with value co-creation for capital providers and senior management, and value co-destruction for low-autonomy employee groups, consumers in privacy-sensitive product categories, and marginalized communities.

This prediction formalizes the systematic review of Lin and Lam, which found conflicting effects across stakeholder groups, and the Mirbabaie et al. empirical work showing AI identity threat in the workplace (Lin & Lam, 2025; Mirbabaie et al., 2021).

Proposition 6. The net value outcome (V) for any given stakeholder group is moderated by the stakeholder governance architecture (G) surrounding the AI deployment.

In other words, good governance can convert partially co-destructive deployments into co-creative ones, while poor governance converts even technically beneficial deployments into co-destructive ones (Papagiannidis et al., 2025; Visconti et al., 2023).

5.4 Affected Stakeholders

Proposition 7. Among affected stakeholders (α), communities and marginalized groups will exhibit the largest gap between value co-creation and value co-destruction under current AI governance regimes.

This is consistent with qualitative findings that minority, parental, and educator stakeholders voice acute concerns about data overcollection and the repurposing of data for unintended surveillance uses (Shrestha & Joshi, 2025).

Proposition 8. The underrepresentation of supply chain and competitor stakeholders in current AI-and-stakeholders research reflects a measurement gap that AI-augmented stakeholder analysis can close.

This proposition builds on Lin and Lam's observation that AI-stakeholder scholarship has under-considered supplier and competitive dynamics (Lin & Lam, 2025) and on the principle that AI-driven value creation permeates supply networks rather than terminating at firm boundaries (Li et al., 2021; Visconti et al., 2023).

5.5 AI Stakeholder Governance Loop

Proposition 9. Firms that complete the full AI stakeholder governance loop (G: mapping → explanation design → deliberation → feedback) will report higher stakeholder trust scores than firms that complete only the first two stages.

This proposition captures the procedural-responsiveness mechanism emphasized by the legitimacy-as-discourse tradition (Smith et al., 2013) and the responsible-AI governance scholarship (Hoffman et al., 2023; Papagiannidis et al., 2025).

Proposition 10. The effectiveness of the AI stakeholder governance loop is moderated by stakeholder technical literacy, with low-literacy stakeholders requiring additional interpretive infrastructure to participate meaningfully.

This is consistent with the XAI literature, which has shown that explanations must be tailored to the knowledge backgrounds of their recipients (Dwivedi et al., 2022; Hoffman et al., 2023; Langer et al., 2021; Suresh et al., 2021).

Proposition 11. Firms operating across jurisdictions with divergent AI governance regimes (e.g., EU AI Act, UK pro-innovation, U.S. NIST RMF) will exhibit fragmented AI stakeholder governance loops unless they adopt a baseline-of-the-highest-floor strategy.

This is supported by comparative work documenting that "the EU AI Act takes a centralised approach to AI governance, whereas the UK takes a risk-centred approach" (Kiden et al., 2024), making cross-jurisdictional harmonization of stakeholder-engagement practices a real organizational problem (Ribeiro et al., 2025).

Proposition 12. The long-run legitimacy and competitive position of firms will be more strongly predicted by their score on the AI stakeholder governance loop than by their level of AI deployment alone.

This final proposition aggregates the previous eleven into a managerial insight that echoes the central claim of stakeholder theory—managing stakeholders well generates performance benefits—but updates it for the AI era (Freeman, 2004; Visconti et al., 2023).

6. Implications

6.1 Implications for Theory

The model advances stakeholder theory in three ways. First, by extending the theoretical territory to include synthetic stakeholders and algorithmic salience, it provides a vocabulary for a class of actors that the existing theory cannot name (Böhm et al., 2022). Second, by reinterpreting salience as algorithmically produced rather than purely interactional, the model preserves the explanatory power of Mitchell, Agle, and Wood's framework while acknowledging that the attributes of stakeholders are themselves increasingly algorithmically evaluated (Mitchell et al., 1997). Third, by treating value as bi-directional and stakeholder-group-specific, the model aligns stakeholder theory with the rigorous empirical work being done in the AI-and-firm-performance literature (Lin & Lam, 2025; Visconti et al., 2023).

The model also has implications for adjacent theoretical fields. In corporate governance, it aligns with Achanta's call for a dynamic governance model that reconceptualizes fiduciary duties for the digital age (Achanta, 2025). In AI ethics, it provides a structured vocabulary for translating abstract principles (fairness, transparency, accountability) into organizational practices that are sensitive to the specific stakeholder configurations any given firm confronts (Gianni et al., 2022; Ribeiro et al., 2025). In the more-than-human management literature, it offers a more granular treatment of AI than the broader category of "non-humans," treating AI as a particularly consequential subtype that warrants its own theoretical apparatus (Poggioli et al., 2023).

6.2 Implications for Practice

For boards and executives, the model implies three practical moves.

First, map the synthetic stakeholders. Directors should systematically identify AI systems inside their organizations that exercise decision power in ways resembling stakeholder behavior, and assess the ethical, reputational, and operational implications of treating them as quasi-stakeholders in strategic planning (Visconti, 2025a, 2025b).

Second, invest in layered explainability. Because different stakeholders need different explanations, a one-size-fits-all transparency strategy is insufficient. Drawing on the XAI literature, firms should design explanation interfaces for distinct audiences—users, consumers, business deployers, and regulators—each with the depth and format appropriate to their needs (Dwivedi et al., 2022; Hoffman et al., 2023; Langer et al., 2021; Meske et al., 2020).

Third, build stakeholder-specific accountability infrastructure. Algorithmic audits, ethics committees, public disclosure practices, and redress mechanisms should be designed around the most vulnerable stakeholder groups (communities, marginalized customers, employees) rather than only around the most powerful (investors, regulators) (Iseko, 2025; Koene et al., 2019; McGregor et al., 2019).

6.3 Implications for Policy and Regulation

For policymakers, the model supports a stakeholder-aware turn in AI regulation. International debate has gravitated toward either pure principle-setting (Gianni et al., 2022; Giungato et al., 2021) or pure risk-tiering (Ribeiro et al., 2025). A stakeholder-aware approach would add a third dimension—mapping the stakeholder field in which an AI system will operate—and design compliance requirements around the vulnerability profile of the most exposed groups, with attention to communities, employees, and marginalized populations that are typically under-served by procedural protections (Iseko, 2025; Kiden et al., 2024). Comparative regulatory frameworks should pursue a "baseline-of-the-highest-floor" approach rather than forcing firms into lowest-common-denominator designs (Kiden et al., 2024; Ribeiro et al., 2025).

7. Limitations and Future Research

Our model is conceptual, not empirical. The propositions are logically derived but presently untested. We encourage empirical work that operationalizes the constructs and measures relationships across the model's structure. Several specific research streams are particularly promising.

Comparative case studies of AI deployment would help test Propositions 5–6 by tracing value flows across stakeholder groups in single-firm deployments with distinct governance architectures.

Large-sample survey research on stakeholder trust and AI could operationalize Construct 2 (algorithmic salience) and test Proposition 3 by measuring how stakeholders perceive their own salience in algorithmically mediated environments.

Field and lab experiments on XAI could test Propositions 9–10 by comparing stakeholder trust outcomes across firms that complete different stages of the governance loop.

Cross-jurisdictional comparative research on AI governance would be especially valuable for testing Proposition 11, since current regulatory divergence makes natural variation readily observable.

Network studies of AI ecosystems could extend the model beyond the firm boundary to examine how supply chain and competitor stakeholders are affected by AI adoption, addressing a gap that Lin and Lam have flagged (Lin & Lam, 2025).

Interdisciplinary integration with critical-theory traditions—feminist, decolonial, and disability-studies frameworks—could deepen the analysis of which stakeholders are systematically excluded by AI systems and why (Böhm et al., 2022).

We note several limitations of our own framing. The model privileges the firm-level unit of analysis; sectoral and macroeconomic dynamics require extensions we have not pursued here. The model also assumes a relatively stable institutional environment; the rapid emergence of agentic AI systems and multi-agent decision ecosystems may require further revision. Finally, the model under-specifies how cultural context shapes which stakeholders are salient in a given AI deployment; future work should integrate comparative cultural analysis.

8. Conclusion

Stakeholder theory was built for a world in which the actors on the boundary of the firm were human. That world has receded. Today's firms operate in stakeholder fields in which AI systems allocate value, impose obligations, and make decisions that materially shape the welfare of customers, employees, communities, and regulators. The categories of classical stakeholder theory—stakeholder as claimant, stakeholder as design, stakeholder as salience-ranked actor—can still do work, but only if they are extended to incorporate the new actors and the new procedural demands that AI introduces.

We have argued for, and constructed, a conceptual model with five core constructs: synthetic stakeholder, algorithmic salience, value co-creation/co-destruction, affected stakeholder configuration, and the AI stakeholder governance loop. We have derived twelve testable propositions. The model preserves the pragmatic and managerial orientation that Freeman advocated while introducing the analytical vocabulary needed for firms, regulators, scholars, and stakeholders themselves to navigate a stakeholder field in which one of the parties is artificial.

A theory of stakeholders for the twenty-first century must be neither human-centric by default nor technology-deterministic by default. It must theorize, concretely and operationally, what it means to manage value, voice, and accountability in a world where the firms we study—and the people we serve—are entangled with intelligent machines whose autonomy, opacity, and reach decisively reshape the stake everyone has in how business is conducted.

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