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Integrating Human Judgment and Computational Insight: Organizational Intelligence in Digitally Transformed Firms

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Abstract

In an era of rapid digital transformation, organizations confront a fundamental tension: algorithmic systems excel at pattern recognition and predictive efficiency, yet falter when confronted with ambiguity, ethical nuance, and contextual idiosyncrasy. This theory-development article advances a novel conceptualization of organizational intelligence as an emergent property of deliberate integration between human judgment and computational insight. Synthesizing recent scholarship on human–AI collaboration, hybrid decision systems, and the limits of automation, the article argues that digitally transformed firms achieve superior strategic outcomes only when they architect “augmented organizational intelligence”—a hybrid capability that transcends both pure human intuition and standalone machine intelligence. The proposed framework delineates cognitive complementarities, identifies boundary conditions of algorithmic autonomy, and specifies integration mechanisms that enable dynamic synthesis. Five core propositions articulate causal pathways through which human oversight, interpretive layering, and feedback loops convert raw computational output into contextually enriched organizational decisions. By bridging literatures from strategic management, information systems, and organization science, the article offers a conceptual architecture for hybrid intelligence that addresses persistent gaps in understanding how firms can move beyond technology adoption toward genuine cognitive augmentation. Theoretical and managerial implications underscore the need to redesign decision architectures to preserve human agency while harnessing machine scalability, thereby redefining organizational intelligence for the post-digital age.

Keywords Human-AI collaboration, Digital transformation, Organizational intelligence, Hybrid decision-making, Augmented cognition, Computational insight

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Introduction

Digitally transformed firms operate in environments defined by unprecedented velocity, complexity, and uncertainty. Advances in artificial intelligence have enabled the deep embedding of algorithmic systems into core organizational processes, ranging from supply-chain optimization to strategic resource allocation [1–5]. These technologies promise not only efficiency gains but also enhanced predictive capacity and real-time responsiveness [5–8]. However, emerging evidence suggests that purely

algorithmic decision systems often produce brittle outcomes when confronted with incomplete data, shifting stakeholder expectations, or fundamentally novel events [9, 10].

Human judgment, by contrast, retains a unique capacity for intuition, ethical deliberation, and contextual sense-making. It enables decision-makers to interpret ambiguous signals, reconcile competing objectives, and adapt to rapidly evolving conditions. Yet human cognition is inherently bounded—susceptible to biases, inconsistencies, and

limited information-processing capacity. This duality highlights a central paradox of decision-making in the digital age: neither human cognition nor algorithmic computation alone is sufficient to sustain effective organizational intelligence under conditions of high complexity [4, 10].

The central thesis of this article is that organizational intelligence in digitally transformed firms emerges not from the substitution of human judgment by algorithmic systems, nor from their simple coexistence, but from their deliberate and architected integration. Hybrid intelligence is thus conceptualized as a system-level capability arising from the structured interaction between human and computational modes of reasoning [4, 11].

Recent scholarship increasingly points toward this integrative perspective. Early conceptualizations of human–AI symbiosis emphasized the augmentative role of intelligent systems, arguing that machines extend rather than replace human cognition [1]. Building on this foundation, subsequent research has examined the cognitive and behavioral challenges associated with human–algorithm interaction, including issues of opacity, trust calibration, and delegation [9–15]. These studies reveal that the effectiveness of hybrid decision-making depends not merely on the presence of advanced technologies but on how their outputs are interpreted, integrated, and acted upon by human decision-makers [2, 11].

At the same time, empirical and conceptual work demonstrates that firms achieving superior outcomes are those that explicitly design decision architectures to leverage complementarities between human and algorithmic capabilities [5, 12, 13]. Algorithmic systems contribute precision in pattern recognition, scalability in data processing, and consistency in execution [7, 8]. Human actors contribute interpretive synthesis, contextual awareness, and value alignment. The performance advantages observed in digitally advanced firms, therefore, stem from the interaction between these capabilities rather than from either in isolation [5, 13].

The limitations of purely algorithmic approaches have become increasingly salient. While machine learning models excel in environments with stable data distributions and well-defined objectives, they struggle in situations that require analogical reasoning, ethical judgment, or the interpretation of weak and emergent signals [9, 14–20].

Moreover, reliance on automated outputs introduces risks, such as automation bias, in which human decision-makers defer excessively to algorithmic recommendations even in the presence of contradictory contextual information [10]. Conversely, reliance on unaided human judgment in data-rich environments leads to scalability constraints, inconsistent decision quality, and missed opportunities for predictive insight [21–24].

Taken together, these observations point toward a hybrid paradigm in which organizational intelligence is reconceptualized as an emergent property of socio-technical systems. In this view, intelligence does not reside solely in individuals or technologies but arises from the structured interaction between them, mediated by organizational processes and decision architectures [4, 11].

This article addresses a critical theoretical gap in this emerging domain. Despite the rapid proliferation of research on human–AI collaboration, existing studies remain fragmented across disciplinary boundaries. Strategic management research has emphasized dynamic capabilities and competitive advantage [5, 8], information systems scholarship has focused on technology adoption and user interaction [10, 11], and organization science has examined team-level coordination and cognition [9, 25]. However, few studies provide an integrative theoretical framework that explains how micro-level complementarities between human judgment and algorithmic insight scale into macro-level organizational intelligence within digitally transformed firms [11, 13].

To address this gap, the present study develops a unified conceptual model of hybrid organizational intelligence. It delineates the architectural mechanisms through which human and computational capabilities are integrated, specifies the conditions under which their complementarities are realized, and advances a set of propositions linking hybrid decision systems to organizational outcomes [5, 13, 17]. In doing so, the article contributes to a more comprehensive understanding of how firms can design and govern augmented intelligence systems that are not only efficient but also adaptive, interpretable, and aligned with organizational values [25, 26].

The present theory-development effort responds to this lacuna by proposing a process-oriented framework centered on hybrid decision architectures. It synthesizes insights from peer-reviewed research focusing on human–

AI collaboration, augmented intelligence, and the boundaries of algorithmic decision-making [1, 11, 17]. The article proceeds as follows. First, theoretical foundations are synthesized to establish the cognitive foundations of human and machine intelligence and their documented interactions. Second, a new theory of hybrid organizational intelligence is articulated through five propositions that specify causal mechanisms and boundary conditions. A mandatory conceptual figure illustrates the proposed architecture, highlighting parallel processing streams, integration layers, and feedback loops. Throughout, Vancouver-style numeric citations anchor the arguments in the compiled reference set.

By developing this theory, the article contributes to digital business and management studies in three ways. First, it reframes organizational intelligence as a relational, hybrid construct rather than an attribute of either humans or machines. Second, it specifies actionable design principles for decision architectures that digitally transformed firms can implement. Third, it offers testable propositions that future empirical work can validate [17, 27]. In doing so, the article equips scholars and practitioners with a conceptual lens for navigating the next frontier of digital transformation—one in which competitive advantage accrues to organizations that master integrating human judgment and computational insight.

Theoretical Foundations

The foundations of the proposed theory rest on three interlocking streams of research: the distinct cognitive architectures of human judgment and algorithmic processing, the documented complementarities that arise when these architectures interact, and the persistent limitations that constrain purely automated systems [4, 11, 13].

Human judgment is characterized by holistic, context-sensitive processing. Drawing on experiential knowledge and analogical reasoning, individuals excel at sensing weak signals, interpreting ambiguous cues, and applying ethical or stakeholder-oriented lenses [22, 23]. Algorithmic systems, conversely, operate through statistical optimization and pattern recognition at scales unattainable by humans [7, 8]. Recent studies illustrate this cognitive divide. For instance, research on AI-augmented strategic decisions shows that machine models outperform humans in predictive accuracy on structured data yet underperform

when contextual or value-based factors dominate [7, 8, 23]. Similarly, investigations into managerial professions reveal that human–AI teams achieve higher-quality outcomes precisely because humans supply interpretive flexibility that algorithms lack [2, 3].

Complementarities emerge when firms deliberately pair these strengths. Literature on human–AI teaming demonstrates that dynamic capabilities are enhanced when organizations cultivate “human-AI skills” and embed them within supportive digital cultures [5, 6]. Configurational analyses further indicate that managerial beliefs about collaboration moderate the effectiveness of such pairings, particularly in supply-chain contexts [12]. Strategic decision-making research extends this insight, showing that generative AI tools improve evaluation of strategic alternatives only when paired with human oversight that corrects for model hallucinations or value misalignment [8, 13].

Yet the literature also documents clear boundaries to algorithmic autonomy. Opacity remains a central challenge: professionals frequently disengage from AI recommendations when they cannot trace the reasoning behind outputs, leading to under-utilization of valuable computational insight [9]. Cognitive delegation studies identify “productive delegation” pathways but warn that poor interface design exacerbates confirmation bias and automation complacency [10]. Empirical work on human-machine behaviors in intelligent environments further reveals “catastrophe” mechanisms—sudden breakdowns in hybrid performance—when feedback loops are absent or misaligned [16].

Organizational intelligence in digital transformation, therefore, cannot be reduced to technology adoption. Instead, it requires explicit architectures that orchestrate parallel processing streams [4, 11]. Systematic reviews of human–AI collaboration emphasize the need for integrative models that move beyond dyadic interactions to system-level synthesis [11, 14]. Recent contributions highlight the moderating roles of organizational culture, leadership beliefs, and innovation climates in enabling such synthesis [6, 17]. Studies of new product development, cyberloafing, and strategic alliances collectively underscore that hybrid systems succeed when they preserve human agency while scaling computational capacity [15, 19, 26].

Taken together, these streams reveal an emerging consensus: organizational intelligence is an emergent

property of hybrid cognition [4, 11, 13]. The present theory builds upon this consensus by specifying the mechanisms through which integration occurs and the conditions under which it yields superior outcomes. By synthesizing the references, the framework bridges micro-level cognitive processes with macro-level organizational capabilities, offering a coherent foundation for the propositions that follow.

Hybrid Organizational Intelligence: Architectures for Human–Algorithm Integration

Human judgment versus algorithmic insight

Human cognition and algorithmic processing rest on fundamentally distinct epistemological and operational foundations. Human judgment is inherently integrative, drawing simultaneously on affective cues, tacit knowledge, ethical reasoning, and situational context [22, 23]. It is capable of navigating ambiguity, reframing ill-structured problems, and assigning meaning where formal models lack representational capacity. In contrast, algorithmic systems operate through formalized representations, optimizing within predefined parameter spaces using statistical inference, pattern recognition, and computational scalability [7, 8].

This divergence generates a productive tension. While algorithms excel in consistency, speed, and scalability, they remain bounded by the assumptions embedded in their design and training data [9, 20]. Human cognition, although subject to bias and bounded rationality, retains a unique capacity for contextual adaptation and moral evaluation [24]. The interplay between these modes of intelligence thus creates both friction—stemming from mismatched logics—and opportunity—arising from their complementary strengths [4, 10].

Complementarities in decision systems

When deliberately orchestrated, human and algorithmic capabilities function not as substitutes but as mutually reinforcing components of a broader decision system. Algorithmic insight contributes to high-volume data processing, probabilistic forecasting, and pattern detection across dimensions that exceed human cognitive limits [7, 8]. Human judgment, in turn, contributes interpretive depth,

sensemaking, and the capacity to reframe decision premises in light of evolving goals or values [22, 23].

Crucially, complementarities emerge not merely from coexistence but from structured interaction. Human actors interrogate, contextualize, and selectively override algorithmic outputs, while algorithms extend human cognition by surfacing latent structures and counterintuitive relationships [5, 13]. This reciprocal augmentation transforms decision-making from a linear process into a dynamic, iterative exchange between computational and cognitive domains [4, 11].

Limitations of purely algorithmic approaches

Despite their strengths, purely algorithmic systems encounter irreducible limitations, particularly in environments characterized by novelty, ambiguity, and ethical complexity [9, 20]. Algorithms rely on historical data distributions and formalized objective functions; when confronted with unprecedented scenarios or shifting value landscapes, their outputs may become unreliable or misaligned with organizational intent [20].

Moreover, algorithmic opacity—often intensified by complex machine learning models—can obscure underlying assumptions and reduce accountability [9]. Over-reliance on automated outputs may also induce automation bias, whereby decision-makers defer to algorithmic recommendations even when contradictory evidence is available [10]. Collectively, these limitations introduce systemic fragility, especially in high-stakes or rapidly evolving contexts [16].

Table 1 clarifies the distinct cognitive contributions, isolated failure risks, and integrative value pathways that underpin augmented organizational intelligence.

Table 1. Cognitive complementarity and failure logic in hybrid organizational intelligence

Decision dimension	Human judgment contribution	Computational insight contribution	Failure when isolated
Signal detection	Identifies weak,	Detects latent patterns across	Human over

	ambiguous, and emergent cues through contextual awareness	large-scale structured data	scale-regula algori miss s conte anom		contested contexts		des trac
				Learning from outcomes	Extracts experiential lessons, revises mental models, and updates judgment heuristics	Retrains models using performance data and feedback signals	Hur learnin be sele algori learnin reinf flawed
Problem framing	Reframes ill-structured issues and revises assumptions in light of changing goals	Stabilizes framing through formal variables, measurable indicators, and predictive structure	Human fra inconsi algori inherit prede objec				
Ethical evaluation	Incorporates fairness, legitimacy, stakeholder sensitivity, and moral reasoning	Can operationalize rule-based constraints and monitor consistency at scale	Human in etl consis algori optim with norm underst		Connects decisions to long-term intent, organizational values, and political realities	Aligns recommendations with measurable objectives and optimization routines	Human dr strateg algori ove proxi targ
Decision speed	Enables rapid action under uncertainty through intuition and experiential recognition	Processes vast data rapidly and generates near-real-time recommendations	Human unc compl algori accel low-q outputs misali				
Adaptation to novelty	Uses analogical reasoning and situational improvisation when precedent is weak	Performs best when novel cases resemble prior training distributions	Human overger fro anec algorith unc distrib sh				
Accountability	Supports justification, explanation, and responsibility attribution in	Produces traceable logs, thresholds, and decision records	Human rationa be t algori logic n opa				

Hybrid intelligence in organizations

To address these limitations, organizations increasingly adopt hybrid intelligence architectures that integrate human and algorithmic capabilities into cohesive decision systems [5, 13, 25]. Effective integration is not achieved through simple layering but through deliberate architectural design that preserves the distinct strengths of each mode while enabling meaningful synthesis [4, 11].

Such architectures typically involve parallel processing streams—algorithmic analysis and human interpretation—linked through a synthesis layer that combines, evaluates, and translates outputs into actionable decisions [11, 13]. The effectiveness of hybrid intelligence depends critically on the design of this integration layer, including interfaces, governance structures, and protocols for escalation, override, and learning [10, 25].

Importantly, hybrid systems are not static configurations but adaptive infrastructures. They evolve through continuous interaction, as both human actors and computational models learn from outcomes and refine their contributions over time [17, 27].

Propositions

Building on the preceding theoretical arguments, the following propositions articulate the core mechanisms through which hybrid organizational intelligence emerges and generates performance advantages.

Proposition 1

In digitally transformed firms, the deliberate pairing of human contextual reasoning with algorithmic pattern recognition produces augmented organizational intelligence that exceeds the performance of either mode in isolation [1, 7, 23].

This proposition reflects a superadditive logic of complementarities. Algorithmic systems contribute scale, speed, and predictive accuracy, while human cognition contributes contextual interpretation and adaptive reframing. When deliberately integrated, these capabilities generate a form of augmented intelligence that is qualitatively distinct from, rather than merely additive to, its components.

Proposition 2

Hybrid decision architectures moderate the relationship between digital transformation intensity and strategic outcome quality, with integration layers serving as critical mediators [5, 10, 17].

Digital transformation alone does not guarantee improved strategic outcomes. Instead, its effects depend on how effectively algorithmic outputs are integrated into organizational decision-making processes. The integration layer—where human and computational inputs are synthesized—functions as a mediating mechanism that translates technological capability into realized performance.

Proposition 3

The presence of explicit feedback loops between integrated decisions and both human and computational subsystems accelerates organizational learning and mitigates automation bias [9, 16, 27].

Feedback loops serve as dynamic learning mechanisms. They enable algorithms to update based on realized outcomes and allow human decision-makers to calibrate their trust in algorithmic recommendations. By institutionalizing such loops, organizations reduce the risk

of uncritical reliance on automated outputs and foster a more reflexive, learning-oriented decision environment.

Proposition 4

Limitations of algorithmic opacity are attenuated when organizations institutionalize human interpretation protocols within the decision synthesis layer [11, 18, 25].

Algorithmic opacity can undermine accountability and trust. However, structured interpretation protocols—such as model interrogation, explanation routines, and cross-functional review—enable human actors to contextualize and validate algorithmic outputs. These practices transform opacity from a barrier into a manageable condition.

Proposition 5

Complementarities between human judgment and computational insight are strongest under conditions of high environmental volatility, where contextual reasoning compensates for model extrapolation failures [8, 13, 24].

Environmental turbulence amplifies the limits of algorithmic generalization. In such contexts, human judgment plays a critical compensatory role by identifying anomalies, reinterpreting signals, and adjusting decision frames. The value of hybrid intelligence thus increases as environmental predictability decreases.

Proposition 6

Organizations that embed ethical oversight and value alignment within hybrid architectures achieve sustainable competitive advantage through responsible augmented intelligence [2, 4, 26].

Beyond performance, hybrid intelligence must be aligned with organizational values and societal expectations. Embedding ethical oversight mechanisms—such as governance frameworks, accountability structures, and fairness checks—ensures that augmented intelligence is deployed responsibly, thereby enhancing legitimacy and long-term competitiveness.

Hybrid Organizational Intelligence Architecture

Figure 1 presents the hybrid organizational intelligence architecture, showing how computational analysis and

human judgment converge through a decision synthesis layer to generate augmented organizational intelligence.

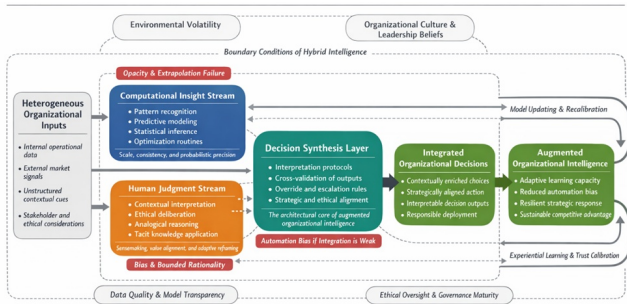


Figure 1. Hybrid organizational intelligence architecture in digitally transformed firms. The figure depicts organizational intelligence as an emergent capability generated through the structured integration of computational insight and human judgment within a central decision synthesis layer, reinforced by bidirectional feedback loops and conditioned by environmental, organizational, technological, and ethical contingencies.

At the input stage, heterogeneous data streams—internal operational data, external market signals, and unstructured contextual information—are ingested into algorithmic analysis layers. These layers apply machine learning, statistical modeling, and optimization techniques to generate predictive, diagnostic, and prescriptive outputs.

These outputs do not directly determine decisions. Instead, they are routed into a decision synthesis layer, where human actors engage in interpretation, contextualization, and critical evaluation. Within this layer, algorithmic recommendations are assessed against strategic objectives, organizational knowledge, and ethical considerations. This process transforms raw predictions into actionable insights.

The resulting integrated decisions embody both computational rigor and interpretive nuance. Importantly, the architecture is sustained by bidirectional feedback loops. Decision outcomes feed back into algorithmic systems for model updating and into human subsystems for experiential learning and judgment calibration. Over time, this recursive structure enables continuous adaptation, reducing error propagation and enhancing organizational resilience.

Thus, the architecture functions not as a static pipeline but as an evolving socio-technical system in which learning, adjustment, and integration are ongoing processes.

Boundary Conditions of Hybrid Organizational Intelligence

Hybrid intelligence architectures are inherently contingent. Their effectiveness depends on a set of boundary conditions that shape the relative contribution, interaction, and dominance of human and algorithmic components. These conditions determine when complementarities are realized and when tensions or inefficiencies may emerge.

First, environmental characteristics—such as volatility, complexity, and uncertainty—directly influence the value of human interpretive capacity relative to algorithmic prediction. Second, organizational factors—including decision rights, expertise distribution, and cultural attitudes toward technology—affect the quality of integration within the synthesis layer. Third, technological conditions—such as data quality, model transparency, and system interoperability—shape the reliability and usability of algorithmic outputs.

Together, these boundary conditions define the operational envelope within which hybrid organizational intelligence can generate superior outcomes. Understanding these contingencies is therefore essential for both theoretical development and practical implementation.

Table 2 specifies the boundary conditions, architectural levers, and governance responses that determine whether hybrid decision systems produce responsible and sustainable organizational intelligence.

Table 2. Boundary conditions and design levers for responsible hybrid intelligence

Boundary condition	High-risk manifestation	Consequences of hybrid intelligence	Architectural design
Environmental volatility	Rapid market discontinuities, novel events, and unstable causal patterns	Algorithmic predictions become brittle; human interpretation becomes more decisive	Incorporating human expertise to escape rigid scenarios based on a synthetic landscape

Task ambiguity	Ill-structured problems, conflicting objectives, and non-quantifiable trade-offs	Pure optimization logic becomes insufficient for valid decision-making	En inter re proto multi jud chec	Ethical oversight maturity	No fairness review, weak value alignment, and absent accountability structures	Performance gains come at the cost of legitimacy and long-term sustainability	Inte ethics value and trigg arch
Data quality maturity	Incomplete, biased, delayed, or weakly integrated data inputs	Computational recommendations become unreliable or misleading	Adv vali gate cont sig be syn	Feedback-loop strength	No systematic outcome review or weak bidirectional learning	Automation bias persists, and both subsystems learn slowly	Estab fee chan m retrai hu jud recal
Model transparency	Opaque or weakly explainable outputs	Human actors disengage, over-defer, or misinterpret recommendations	Institu expl rou cha sessio trac inte	System interoperability	Fragmented platforms, weak interfaces, disconnected workflows	Integration remains symbolic rather than operational	De inter inte con data, and c rou
Organizational culture	Technocentric bias, distrust of AI, siloed expertise, weak collaboration norms	Integration quality deteriorates, and complementarities remain unrealized	Build func syn tear sh hun de ne	Environmental volatility as a catalyst for complementarities Under conditions of high environmental turbulence, the value of hybridization becomes particularly pronounced. Algorithmic systems, trained on historical data, often struggle to accommodate abrupt shifts in market dynamics, technological trajectories, or stakeholder expectations. In such contexts, their predictions may become brittle or systematically biased. Human judgment, by contrast, retains the capacity for rapid sensemaking, analogical reasoning, and contextual reinterpretation. It enables organizations to question underlying assumptions, incorporate weak signals, and adapt decision frames in real time. As a result, human contextual reasoning compensates for model extrapolation failures, transforming potentially fragile algorithmic outputs into resilient strategic responses. This dynamic underscores the conditional nature of complementarities: the greater the environmental volatility, the more critical the role of human interpretive capacity in sustaining effective decision-making.			
Expertise distribution	Insufficient domain expertise or weak AI literacy among decision actors	Poor interrogation of outputs and ineffective use of computational insight	Deve sp augm skil inte tra				
Decision rights structure	अस्पष्ट ownership, over-centralization, or no clear override authority	Delays, conflict, and accountability gaps emerge within the synthesis layer	Defin ove esca & adju pro				

Organizational culture and leadership beliefs as moderators

Digital organizational culture functions as a critical moderator. Firms that embed “human-AI skills” and foster managerial beliefs that favor collaboration experience stronger synergies between the two cognitive modes. Conversely, cultures marked by technocentric bias or residual “not-invented-here” syndrome attenuate integration benefits, leading to underutilization of computational insights or premature rejection of algorithmic outputs.

Technological maturity and data quality constraints

Even the most sophisticated integration layer cannot overcome foundational data deficiencies or model opacity. When algorithmic systems lack explainability, human interpretation protocols must be institutionalized to prevent disengagement.

Designing Integration Mechanisms for Augmented Organizational Cognition

Effective hybrid intelligence requires deliberate design of three interlocking mechanisms: parallel processing streams, synthesis protocols, and adaptive feedback loops.

Parallel processing and the integration layer

Rather than sequential hand-offs, the architecture maintains simultaneous operation of human and computational subsystems. Data enters algorithmic analysis while human actors simultaneously engage in sense-making. The central integration layer then performs decision synthesis—weighting algorithmic confidence scores against human-assigned contextual valuations. This layered approach prevents both automation bias and intuition-driven scalability failures.

Institutionalizing human oversight and ethical guardrails

Human oversight is not residual but constitutive. Protocols for interpretation, value alignment, and ethical adjudication must be codified within governance structures. Recent

configurational research demonstrates that such institutionalization transforms potential opacity challenges into opportunities for enriched judgment.

Feedback loops and continuous co-evolution

Mutual learning is essential. Integrated decisions feed back into both subsystems: algorithmic models are retrained on human-adjusted outcomes, while human actors refine their mental models through exposure to machine-generated patterns. These loops accelerate organizational learning, progressively elevating baseline intelligence.

The six propositions articulated earlier gain specificity when viewed through these design lenses. Proposition 1 is realized precisely when parallel streams converge within a robust synthesis layer. Proposition 2 holds because integration mechanisms mediate the transformation of digital transformation intensity into measurable strategic gains. Propositions 3 and 4 underscore the necessity of feedback and interpretation protocols, while Propositions 5 and 6 highlight volatility and ethical alignment as boundary conditions that amplify or attenuate the architecture as a whole.

Augmented organizational intelligence: Pathways to responsible competitive Advantage

When properly architected, hybrid systems produce an emergent capability—augmented organizational intelligence—that is qualitatively superior to either standalone human or machine cognition. This intelligence is relational, adaptive, and ethically grounded. It enables firms to sense weak signals at scale, interpret ambiguous futures, and align decisions with evolving stakeholder values. Competitive advantage accrues not merely from technology adoption but from the mastery of integration itself. Organizations that treat hybrid architectures as dynamic capabilities rather than static tools achieve sustained differentiation in digitally transformed markets.

The framework also carries important caveats. Without deliberate design, hybrid attempts can devolve into fragmented decision-making or new forms of cognitive overload. Therefore, managerial attention must shift from “implementing AI” to “orchestrating human–algorithm symbiosis.”

Conclusion

This theory-development article has advanced a novel conceptualization of organizational intelligence as the emergent outcome of architected integration between human judgment and computational insight. By synthesizing three decades of cumulative scholarship into a coherent process-oriented framework, the article delineates cognitive complementarities, boundary conditions, integration mechanisms, and design principles that collectively define augmented organizational intelligence.

For scholars, the framework opens multiple avenues: longitudinal studies of feedback-loop efficacy, comparative analyses of integration maturity across firm types, and investigation of ethical guardrails in high-stakes domains. For practitioners, the practical design principles translate directly into decision-architecture redesign, governance protocols, and capability-building initiatives.

Ultimately, the post-digital competitive landscape will belong to organizations that master the delicate balance of preserving human agency while harnessing machine scalability. Organizational intelligence, once viewed as an attribute residing within individuals or algorithms, is reconceived here as a systemic, hybrid capability. By integrating human judgment and computational insight,

digitally transformed firms do not merely become faster or more efficient—they become wiser. This augmented wisdom, grounded in deliberate architectural choices, represents the next frontier of sustainable advantage in an increasingly complex and uncertain world.

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