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SYNTHETIC KNOWLEDGE AS SYSTEMIC CAPITAL IN THE GOVERNANCE OF GENERATIVE ARTIFICIAL INTELLIGENCE

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Purpose: The diffusion of generative artificial intelligence signals a structural transformation in the architecture of the knowledge economy. While prior research has focused primarily on automation and augmentation (Raisch, Krakowski, 2021; Shrestha et al., 2019), the systemic implications of generative systems for knowledge as capital remain insufficiently theorized. This paper aims to conceptualize synthetic knowledge as systemic capital and to explain its implications for organizational quality, governance and sustainability.
Design/methodology/approach: This paper conceptualizes synthetic knowledge as systemic capital, that is, algorithmically generated cognitive content produced within concentrated digital infrastructures and mobilized within organizations. Unlike traditional knowledge capital, held by identifiable members of a firm and integrated through processes the firm controls, synthetic knowledge is externally generated, infrastructurally mediated, and materially constrained. Drawing on the knowledge-based view of the firm (Grant, 1996), socio-technical transition theory (Geels, 2002; Markard et al., 2012), and recent scholarship on foundation models and the governance of artificial intelligence (Bommasani et al., 2021, 2024; Burkhardt, Rieder, 2024), the study identifies key structural dynamics of synthetic knowledge production.
Findings: The study identifies three structural tensions: cognitive efficiency versus epistemic autonomy, decentralized access versus infrastructural concentration, and digital productivity versus environmental sustainability.
Research limitations/implications: This study is conceptual in nature and does not rely on primary empirical data; the framework requires validation across sectors and organizational forms.
Practical implications: The findings highlight the need for organizations to develop governance mechanisms for managing synthetic knowledge and epistemic dependencies.
Social implications: The study emphasizes the broader societal importance of responsible governance of artificial intelligence and of attention to sustainability.
Originality/value: The article develops a conceptual framework linking infrastructural concentration, epistemic asymmetry, organizational quality, environmental externalities, and regulatory governance, including the European Artificial Intelligence Act. It argues that generative artificial intelligence should be understood not as a neutral tool but as a reorganization of cognitive capital embedded in infrastructural and ecological constraints.
Keywords: synthetic knowledge; generative artificial intelligence; epistemic asymmetry; organizational quality; governance; sustainability.
Category of the paper: Conceptual paper.

1. Introduction

The contemporary knowledge economy is undergoing a structural transformation driven by the diffusion of generative artificial intelligence. Large language models and foundation models increasingly support decision-making, innovation, and knowledge-intensive work (Bommasani et al., 2021; Dwivedi et al., 2023). Yet management research continues to interpret artificial intelligence primarily through automation, augmentation, and algorithmic control (Raisch, Krakowski, 2021; Shrestha et al., 2019; Kellogg et al., 2020). Less attention has been paid to how generative artificial intelligence reshapes the architecture of knowledge as capital.

Within the knowledge-based view of the firm, the firm is an institution for integrating the specialized knowledge held by its individual members (Grant, 1996), while a second line within the same literature admits the collective knowledge of social groups and treats knowledge as a process (Spender, 1996). Competitive advantage derives from integrating competencies, routines, and learning processes, while organizational learning theories emphasize reflexivity and adaptation as foundations of quality and long-term development (Argyris, Schön, 1978; Senge, 1990; Nonaka, 1994). Knowledge capital, in this perspective, remains largely subject to managerial governance.

Generative artificial intelligence disrupts this configuration. Synthetic knowledge, algorithmically recombined content produced within large-scale computational infrastructures, originates outside the firm and is integrated into internal processes. Knowledge production becomes partially externalized: instead of emerging primarily through collective learning, it is accessed through prompts and platform-mediated interfaces. The locus of cognitive production shifts from organizational practice to infrastructural systems operating at planetary scale.

For the purposes of this article, synthetic knowledge is understood as algorithmically generated and organizationally mobilized cognitive content produced by generative artificial intelligence systems on the basis of large-scale model architectures, training data, optimization procedures, and user prompts. Unlike ordinary digital information or automated data processing, it produces linguistically intelligible, context-sensitive and decision-relevant outputs that can be incorporated into organizational reasoning, planning, communication, innovation, and quality governance. This understanding is consistent with recent research on artificial knowledge generation, which shows that generative artificial intelligence introduces a machine-mediated dimension into knowledge management and challenges traditional models of knowledge creation (Alavi, Leidner, Mousavi, 2024; Cerchione, Liccardo, Passaro, 2026). Synthetic knowledge is therefore not knowledge in the classical epistemological sense of justified true belief. Setting truthfulness aside as the defining attribute is not new to organization theory: Nonaka (1994) invoked that classical definition only to shift its emphasis toward justification, understood as a process of convergence and screening carried out within an organization. Synthetic knowledge is a functional organizational resource: a probabilistic, model-mediated cognitive output that becomes knowledge-like when used within managerial and institutional decision processes.

This shift aligns with analyses of platform capitalism and data-driven accumulation (Srnicek, 2017; Zuboff, 2019). Platforms function as organizational forms oriented toward data extraction and infrastructural control, while foundation models mediate access to computationally generated cognition (Burkhardt, Rieder, 2024). Organizations thus rely on outputs whose training regimes and optimization logics remain only partially transparent. Such dependence generates epistemic asymmetry and redistributes cognitive authority beyond firm boundaries.

At the same time, synthetic knowledge is materially grounded. Training and deploying large-scale models require energy-intensive data centers and global hardware supply chains (Strubell et al., 2019; Patterson et al., 2021). From a socio-technical transition perspective (Geels, 2002; Markard et al., 2012), generative artificial intelligence is embedded in socio-technical regimes that include energy supply rather than standing apart from them. Cognitive efficiency coexists with material expansion and environmental cost.

These dynamics coincide with a regulatory turn. The European Artificial Intelligence Act (European Union, 2024) introduces a risk-based governance architecture focused on transparency and accountability. Scholarship increasingly links artificial intelligence risks to institutional responsibility (Wirtz et al., 2022), while policy debate on foundation models turns on how the manner of model release affects competition and the innovation ecosystem (Bommasani et al., 2024). Synthetic knowledge cannot be treated as a neutral productivity tool; it embeds organizations in infrastructures characterized by concentration, opacity, and environmental impact.

Despite growing scholarship, the transformation of knowledge as capital under conditions of infrastructural concentration and ecological constraint remains theoretically fragmented. Automation, digital transformation, governance, and sustainability are often examined separately. Their interdependence has yet to be theorized in systemic terms.

Although recent literature has increasingly addressed generative artificial intelligence in knowledge management, foundation model governance and digital transformation, these debates remain only partially integrated from the perspective of management and quality sciences. Existing studies identify the disruptive role of generative artificial intelligence in knowledge processes and emphasize the need for further conceptual models and empirical research (Strelau, 2025; Cerchione, Liccardo, Passaro, 2026). However, the literature still insufficiently explains how generative systems transform knowledge capital when cognitive outputs are produced outside the firm, within concentrated computational infrastructures, and then incorporated into organizational decision-making under conditions of epistemic opacity and environmental constraint. This article addresses this gap by conceptualizing synthetic knowledge as systemic capital.

The aim of this article is to conceptualize synthetic knowledge as systemic capital and to explain its implications for organizational quality, governance and sustainability under conditions of infrastructural concentration and epistemic asymmetry.

The article addresses three research questions:

RQ1: How does generative artificial intelligence transform knowledge from an organizational resource into infrastructurally mediated systemic capital?

RQ2: How does epistemic asymmetry emerge under conditions of dependence on foundation model infrastructures?

RQ3: How do infrastructural concentration, governance and environmental constraints interact in shaping synthetic knowledge?

This paper argues that generative artificial intelligence represents a structural reconfiguration of knowledge production and mobilization. When knowledge is generated within concentrated computational infrastructures and accessed through platform-mediated architectures, organizations do not simply extend their capabilities; they become embedded in external systems whose material and political conditions exceed their direct control.

2. Methodological Approach

This article is conceptual in nature and follows a theory-building approach based on integrative literature synthesis. In the terms proposed by Jaakkola (2020), the design corresponds to theory synthesis, in which concepts drawn from separate literatures are integrated to account for a phenomenon that none of them explains on its own. It does not test empirical hypotheses through primary data collection. Instead, it develops a conceptual framework by analytically integrating three research streams: the knowledge-based view of the firm and organizational learning, socio-technical transition theory, and recent scholarship on foundation models, artificial intelligence governance and sustainability. Such an approach is justified when the aim of the study is not to measure an already stabilized phenomenon, but to clarify emerging constructs, identify relationships between fragmented debates and propose a theoretical model for future empirical testing. Conceptual articles are particularly relevant when emerging phenomena require theoretical clarification before mature indicators and standardized measurement procedures can be developed (Gilson, Goldberg, 2015; Jaakkola, 2020).

The analysis proceeded in three stages. First, the article reviewed foundational contributions on knowledge as an organizational resource and source of competitive advantage. Second, it examined contemporary research on generative artificial intelligence, foundation models, algorithmic governance, infrastructural concentration and environmental externalities. Third, it synthesized these strands into a multi-layered conceptual model linking infrastructural production, epistemic mediation, organizational quality, systemic externalities and regulatory governance. The value of this approach lies not in statistical generalization, but in conceptual integration, theoretical clarification and the formulation of propositions that may guide future empirical research. The limits of the procedure are those of any conceptual design and are stated in section 13.2.

3. Knowledge as Capital in Management and Quality Sciences: From Organizational Resource to Systemic Architecture

Within management and organization theory, knowledge has long been treated as a strategic organizational resource. The knowledge-based view of the firm posits that sustainable competitive advantage derives from the integration and application of the specialized knowledge held by individual members, coordinated through rules and directives, sequencing, routines, and group problem solving (Grant, 1996). Each of these mechanisms presupposes common knowledge, among them shared language, shared meaning and mutual recognition of one another's knowledge domains, which together allow specialists to combine what they know without transferring it in full. Kogut and Zander (1992) held that what firms do better than markets is the sharing and transfer of the knowledge of their members, and proposed an account of firm boundaries that does not appeal to opportunism. Together, these contributions established knowledge as a central explanatory variable in strategic management and positioned the firm as the primary locus of cognitive coordination.

Importantly, knowledge was never regarded as static. Nonaka's (1994) theory of knowledge creation emphasized the dynamic interplay between tacit and explicit knowledge, highlighting dialogue and shared experience as drivers of innovation. Dynamic capabilities theory further argued that competitiveness rests on distinctive processes for coordinating and combining resources, on the asset positions a firm holds, among them its portfolio of difficult-to-trade knowledge assets, and on the evolution paths it has inherited (Teece, Pisano, Shuen, 1997). In this tradition, knowledge capital is inseparable from learning, reflexivity, and internal governance. Whether the firm is held to generate its cognitive assets or chiefly to apply them, it is the firm that stewards them.

The assumption that knowledge is created and governed primarily within organizational boundaries has shaped management and quality research. Continuous improvement and organizational excellence are typically conceptualized as internally coordinated processes. Even within networks or ecosystems, ultimate responsibility for knowledge integration remains anchored at the firm level.

The diffusion of generative artificial intelligence introduces a structural shift. Artificial intelligence has often been framed as automation or augmentation (Raisch, Krakowski, 2021), yet its deeper significance lies in the relocation of knowledge production itself. Increasingly, cognitive inputs integrated into organizational processes are generated within external computational infrastructures rather than cultivated through internal learning cycles. Large language models produce synthetic outputs incorporated into planning and strategy without being embedded in organizational experience. The firm is no longer the exclusive site of cognitive production.

Research on artificial intelligence capability defines such a capability as the ability of a firm to select, orchestrate and leverage its own artificial intelligence resources (Mikalef, Gupta, 2021). Once the decisive resource is a model that the firm neither trains nor owns, the same logic must be applied to an asset lying beyond its boundary. Algorithmic systems influence decision structures, evaluation criteria, and control mechanisms (Kellogg et al., 2020), shaping how knowledge is interpreted and operationalized. Knowledge capital thus becomes partially infrastructuralized: generated at scale within concentrated computational systems and deployed within organizational contexts.

This infrastructuralization redefines knowledge mobilization. Organizations increasingly mobilize synthetic outputs trained on globally aggregated data rather than solely transforming internally generated insights. The boundary between internal and external knowledge becomes porous, and validation is mediated through platform architectures. The conditions under which knowledge is produced and governed extend beyond the firm into broader socio-technical systems.

This transformation is consequential for management and quality sciences. If knowledge production is partially externalized, organizational autonomy and quality governance can no longer rely exclusively on internal routines. Quality becomes tied to the governance of interfaces between organizations and algorithmic infrastructures. Transparency, reliability, bias, and systemic dependency move to the center of strategic concern. The knowledge-based view remains analytically powerful, but it requires expansion to incorporate the systemic dimension of cognitive capital in digitally mediated and infrastructurally concentrated environments.

Knowledge as capital must therefore be reconsidered not only as an internal strategic asset but as part of a distributed socio-technical architecture in which production, validation, and valorization span organizational and infrastructural domains. This reconfiguration provides the theoretical basis for conceptualizing synthetic knowledge as systemic capital, that is, as capital whose value and control are shaped not solely by firm-level capabilities but also by the political economy and material conditions of digital infrastructures.

4. Synthetic Knowledge and the Transformation of Value Creation in Knowledge-Intensive Systems

Synthetic knowledge differs fundamentally from expert or experiential knowledge embedded in organizational routines. It does not arise from situated practice, tacit understanding, or cumulative institutional memory. Instead, it is generated through large-scale probabilistic modeling across distributed data corpora (Bommasani et al., 2021). Unlike the knowledge creation processes described in classical organizational theory (Nonaka, 1994), it does not emerge from social interaction or tacit–explicit conversion, but from computational recombination at infrastructural scale.

This ontological distinction reshapes value creation. In the knowledge-based view, firms generate value by integrating internally developed knowledge resources (Grant, 1996). Competitive advantage stems from distinctive combinations of skills and learning processes that are difficult to replicate. Under generative artificial intelligence, however, value increasingly depends on the capacity to mobilize externally generated synthetic outputs. The source of cognitive input shifts from organizational memory toward platform-mediated computation. Value creation moves from knowledge integration toward knowledge interface management.

Research on human–algorithm collaboration indicates that generative systems do more than automate tasks (Raisch, Krakowski, 2021; Dwivedi et al., 2023). They shape strategic framing, structure interpretive horizons, and influence decision alternatives (Shrestha et al., 2019). The architecture of value creation becomes co-produced by organizational actors and algorithmic infrastructures. The firm's role evolves from primary producer of knowledge to orchestrator of distributed cognitive resources.

Foundation models operate as infrastructural platforms whose governance structures shape how knowledge is produced, accessed, and updated (Burkhardt, Rieder, 2024). Epistemic authority is increasingly mediated by algorithmic architectures rather than professional communities or hierarchical expertise. The locus of validation shifts toward infrastructural systems that remain only partially transparent to their users.

This shift generates a structural decoupling between knowledge production and responsibility. Organizations may rely on synthetic outputs without controlling training data regimes, optimization logics, or update cycles. Research on algorithmic management shows how such opacity reshapes authority and accountability (Kellogg et al., 2020). Responsibility for outcomes remains internal, while cognitive processes are externally generated and only partially observable.

Competitive advantage therefore rests less on proprietary knowledge assets and more on epistemic capability, that is, the ability to evaluate, contextualize and govern synthetic knowledge flows. Assessing reliability, detecting bias, and aligning outputs with organizational objectives become core competencies. In knowledge-intensive systems, managing the interface between human judgment and synthetic cognition becomes central to sustained value creation.

The environmental dimension further complicates this transformation. Synthetic knowledge production is computationally intensive and materially embedded in energy-consuming infrastructures (Strubell et al., 2019; Patterson et al., 2021). The apparent immateriality of digital cognition conceals its dependence on hardware, electricity grids, and global supply chains. Efficiency gains may coexist with infrastructural expansion and ecological externalities.

Synthetic knowledge thus reconfigures not only how value is generated but how it is distributed and externalized. The shift from internally embedded knowledge to infrastructurally mediated outputs restructures knowledge-intensive systems across organizational, infrastructural, and ecological domains. Competitive advantage becomes intertwined with platform governance and environmental constraint. This systemic transformation provides the conceptual bridge toward understanding synthetic knowledge as systemic capital.

5. Concentration of Cognitive Capital as a Structural Risk

The expansion of generative language models has not only transformed knowledge production; it has intensified the concentration of cognitive infrastructure. Traditional knowledge resources were dispersed across firms, universities and professional communities, whereas the development and operation of large-scale generative models require substantial computational capacity, proprietary datasets, and advanced engineering expertise. These requirements can be met by only a limited number of globally dominant actors (Bommasani et al., 2021). The material foundations of synthetic knowledge are therefore structurally centralized.

This concentration reflects broader dynamics of platform capitalism. Control over data, models, and computational infrastructures generates asymmetries between infrastructure providers and dependent organizational users (Srnicek, 2017; Kenney, Zysman, 2016). Foundation models function as infrastructural platforms that shape downstream innovation ecosystems and redistribute value toward model owners (Burkhardt, Rieder, 2024). Organizations may integrate synthetic outputs into their operations, yet they remain positioned downstream within hierarchies of infrastructural control.

From a management perspective, this development redefines the locus of cognitive capital. In the classical knowledge-based view, competitive advantage derived from firm-specific capabilities and internally embedded knowledge (Grant, 1996). Under the generative paradigm, critical components of cognitive capital reside outside the organization, within proprietary infrastructures operating at global scale. The firm becomes an integrator of cognitive resources rather than their primary producer.

This relocation produces epistemic asymmetry. Organizations may access synthetic outputs but lack meaningful influence over training data regimes, optimization parameters, update cycles, and embedded assumptions. Unlike classical information asymmetry (Akerlof, 1970), which concerns unequal access to information, epistemic asymmetry concerns unequal control over the architectures that generate and structure knowledge. The asymmetry is procedural and infrastructural.

Epistemic asymmetry can be analytically distinguished from information asymmetry along four dimensions. First, it is architectural rather than transactional: the asymmetry concerns control over model design, training data, optimization objectives and update cycles, rather than unequal possession of information alone. Second, it is procedural rather than episodic: it affects the conditions under which outputs are generated before they enter organizational decision-making. Third, it is interpretive rather than merely informational: it shapes what becomes visible, plausible, prioritized or excluded in organizational cognition. Fourth, it is infrastructural rather than interpersonal: it is embedded in platform architectures and computational infrastructures rather than only in relations between buyers and sellers or principals and agents. Recent research on generative artificial intelligence and epistemic justice similarly indicates that these systems mediate access to knowledge, epistemic agency and knowledge hierarchies across institutional and infrastructural contexts (Olaniyan, Martins, Al Maqrashi, 2026).

Dependence of this kind strains governance structures. Automated decision-making removes the human decision-maker to whom a judgment could previously be appealed, leaving fewer points at which an outcome can be contested (Kellogg et al., 2020). Responsibility remains internal while epistemic control does not.

Technological scaling dynamics reinforce this pattern. Performance improvements in large models often follow power-law relationships with respect to model size, data volume, and computational resources, and a compute-optimal allocation of a fixed budget directs most of any increase toward model size rather than toward data volume or training time (Kaplan et al., 2020). Scaling of this kind privileges actors capable of financing and maintaining very large infrastructures. Concentration thus appears less as a market outcome than as a structural feature of the technological architecture itself.

The resulting configuration is layered. Generative infrastructures occupy an upper tier defined by capital intensity, scale, and platform governance, while organizations operate as downstream integrators of synthetic outputs. This architecture reshapes epistemic authority and the capacity to define legitimate or actionable knowledge. Epistemic pluralism may narrow as dominant architectures standardize interpretive frames, since the defects, biases and blind spots of a small number of upstream models propagate to every application built on them (Bommasani et al., 2021).

Concentration also intersects with environmental constraints. Large-scale training and inference infrastructures require continuous energy inputs (Strubell et al., 2019; Patterson et al., 2021). As computational scale expands, so does reliance on energy-intensive ecosystems.

Concentration therefore entails not only control over knowledge production but also control over resource-intensive infrastructures that shape long-term sustainability trajectories.

Concentration of cognitive capital thereby introduces a new form of dependency. Organizational autonomy can no longer be defined solely in terms of internal capabilities. It must extend to cognitive autonomy, meaning the capacity to evaluate and govern synthetic knowledge within infrastructurally concentrated and environmentally constrained systems.

Recognizing concentration as a structural risk does not imply technological determinism. A technological path frames the choices available without settling in advance which trajectory will be followed (Kenney, Zysman, 2016). What concentration underscores is the need for governance capable of balancing efficiency gains with epistemic plurality, competitive fairness and sustainability. This recognition prepares the ground for a deeper analysis of epistemic asymmetry and cognitive value redistribution.

6. Epistemic Asymmetry and the Redistribution of Cognitive Value

The concentration of generative infrastructures restructures not only knowledge production but also the distribution of cognitive value. As organizations increasingly rely on synthetic outputs in strategic and operational decisions, the processes generating these outputs remain external and only partially transparent. Epistemic asymmetry thus becomes a mechanism of value redistribution.

The asymmetry described in the preceding section operates here as a mechanism of distribution rather than of production. Organizations may access model-generated outputs, yet they do not govern data selection regimes, optimization logics, or scaling strategies (Burkhardt, Rieder, 2024). Cognitive authority is progressively decoupled from organizational boundaries and relocated to infrastructural providers.

This relocation reshapes competitive advantage. In the knowledge-based tradition, firms created value through proprietary capabilities and asset positions accumulated along paths competitors could not easily retrace (Grant, 1996; Teece et al., 1997). Under synthetic knowledge production, value increasingly depends on the capacity to orchestrate externally generated cognitive outputs. Competitive differentiation shifts from knowledge ownership to epistemic governance.

A set of meta-capabilities emerges accordingly: evaluating algorithmic outputs, detecting bias, ensuring contextual alignment, and embedding synthetic knowledge within accountable governance structures. Risk and guideline frameworks developed for the governance of artificial intelligence supply part of the ground for such capabilities (Wirtz et al., 2022), while the range of concerns raised across disciplines indicates how wide the required competence has become (Dwivedi et al., 2023). Epistemic capability becomes a core organizational competence. Firms compete less through accumulation of knowledge assets than through their ability to critically manage synthetic knowledge flows.

At the systemic level, cognitive value is co-produced yet asymmetrically appropriated. Organizations contribute data, usage patterns, and contextual expertise to generative infrastructures, often without commensurate influence over model development or value capture. Infrastructure providers consolidate value through ownership, access control, and platform positioning (Burkhardt, Rieder, 2024). This dynamic reflects broader patterns of data-driven accumulation in platform economies (Zuboff, 2019).

Epistemic asymmetry also affects interpretive diversity. Reliance on similar foundation models may narrow strategic framings and reduce epistemic plurality, constraining innovation trajectories (Bommasani et al., 2021).

The environmental dimension adds further complexity. Economic and strategic benefits of synthetic knowledge are widely distributed, while environmental costs of large-scale training and inference remain concentrated within infrastructural ecosystems (Strubell et al., 2019; Patterson et al., 2021). Accountability becomes blurred as cognitive value and ecological burden are allocated differently.

Epistemic asymmetry is, on this reading, a governance problem rather than a technical one. Quality must include the capacity to preserve interpretive autonomy, critically evaluate synthetic outputs, and align algorithmic integration with transparent and responsible practices.

Synthetic knowledge therefore reconfigures not only who produces knowledge, but how cognitive value is generated, appropriated, and externalized. Epistemic asymmetry emerges as a defining characteristic of contemporary knowledge systems, demanding new organizational capabilities and governance frameworks oriented toward competitive fairness, sustainability, and cognitive plurality.

7. Organizational Quality and Development under Conditions of Epistemic Asymmetry

The concentration of cognitive infrastructure and the redistribution of synthetic knowledge reshape not only competitive dynamics but also the foundations of organizational quality. In classical management thought, quality was associated with internal learning, feedback loops, and continuous improvement (Deming, 1986; Sousa, Voss, 2002). Organizational development presupposed coherence: knowledge production, decision authority, and accountability were embedded within the same institutional boundaries.

Under conditions of synthetic knowledge, this coherence becomes partially decoupled. Organizations integrate externally generated cognitive outputs into strategic and operational processes, while the epistemic conditions of their production remain external. The locus of knowledge generation and the locus of responsibility no longer fully coincide. This structural misalignment introduces new challenges for quality governance.

Organizational quality can no longer be defined solely in terms of procedural compliance or internal efficiency. It must incorporate epistemic capability, exercised within decision processes. Research on algorithmically mediated organizations emphasizes human oversight and structured validation, and distinguishes three structures in which human and machine decisions can be combined: full delegation, hybrid sequential arrangements, and aggregation of human and machine judgments (Shrestha et al., 2019; Wirtz et al., 2022). Synthetic outputs cannot replace internal expertise; they must be embedded within reflexive governance architectures.

From the perspective of dynamic capabilities theory, the processes through which a firm coordinates and combines its knowledge assets increasingly require meta-governance capacities; those assets were characterized as difficult to trade (Teece et al., 1997), whereas an asset rented from an external provider is not. Organizations must not only deploy synthetic knowledge but also assess its reliability, bias structures, and contextual limitations. Competitive advantage becomes tied to the governance of interfaces between human judgment and algorithmic systems.

Algorithmic mediation further reshapes organizational control. Studies of algorithmic management show how decision authority may drift toward data-driven systems, weakening accountability and narrowing interpretive diversity (Kellogg et al., 2020). In this context, quality management must address transparency, auditability, and responsibility for algorithmically supported decisions.

The challenge intensifies when synthetic knowledge informs strategic direction. If multiple organizations rely on similar foundation models, convergence of interpretive frames may reduce epistemic diversity across sectors. Homogenized cognitive inputs increase the risk of correlated errors and systemic fragility. Resilience literature highlights diversity, redundancy, and continuous learning as foundations of adaptive capacity (Duchek, 2020). Under epistemic asymmetry, resilience must extend beyond operational robustness toward epistemic resilience, meaning the capacity to preserve interpretive autonomy despite infrastructural dependence.

These dynamics intersect with sustainability. Generative infrastructures are materially embedded in energy-intensive systems (Strubell et al., 2019; Patterson et al., 2021). Organizational development cannot be evaluated solely through cognitive efficiency or innovation speed; it must account for environmental externalities and infrastructural lock-in effects. Long-term quality includes the material conditions under which knowledge is generated.

Under epistemic asymmetry, organizational development becomes a multidimensional governance challenge. It requires balancing cognitive efficiency with interpretive autonomy, infrastructural dependency with internal capability development, and digital productivity with environmental responsibility. Quality management thus evolves from an operational function into a systemic governance capacity embedded in organizational strategy.

8. Governance Implications: Cognitive Capital and the European Regulatory Turn

The concentration of synthetic knowledge infrastructures and the resulting epistemic asymmetry raise fundamental governance questions. When organizations depend on cognitive resources generated within highly concentrated infrastructures, quality and development can no longer be governed exclusively at the firm level. Governance becomes multi-layered, spanning organizational, infrastructural, and institutional domains.

Contemporary scholarship emphasizes that artificial intelligence governance must integrate transparency, accountability, and risk management at systemic levels (Wirtz et al., 2022). AI systems are not isolated tools but components of socio-technical ecosystems marked by dependency and power asymmetry (Burkhardt, Rieder, 2024). Governance therefore cannot be reduced to procedural compliance; it must address the structural conditions under which knowledge is generated, distributed, and mobilized.

The European Artificial Intelligence Act (European Union, 2024) exemplifies this regulatory turn. By introducing a risk-based framework and obligations concerning documentation, transparency, and human oversight, the Act seeks to reassert institutional control over increasingly autonomous systems. For management theory, this marks a shift: organizations are not passive users of technology but accountable participants in distributed knowledge infrastructures.

However, the European Artificial Intelligence Act should not be interpreted as a complete solution to the structural tensions identified in this article. Its risk-based architecture strengthens transparency, documentation and human oversight, but it remains primarily oriented toward the regulation of systems and uses rather than toward the political economy of cognitive infrastructure itself. Recent analyses of the European model of artificial intelligence governance note that the Act joins risk regulation to the protection of fundamental rights, set within objectives of market harmonization (Hulok, 2025). Its practical operation depends on institutional design, including the European AI Office and codes of practice for general-purpose models, and on its interaction with the General Data Protection Regulation, the Data Act, the Digital Services Act and the Digital Markets Act (Graux et al., 2025). From the perspective developed here, regulatory compliance is necessary but insufficient. Organizations may formally comply with regulatory requirements while still remaining dependent on opaque, concentrated and environmentally intensive infrastructures of synthetic knowledge production.

Debates on foundation model governance reinforce this transformation. Central to policy discussion is the manner in which models are released, and the uneven bearing of regulatory proposals on open and closed models and therefore on competition (Bommasani et al., 2024). Because generative models function as infrastructural platforms, governance must address both downstream applications and upstream architectures. Cognitive capital is embedded within layered regimes of ownership, access, and control.

For management and quality sciences, this development redefines organizational responsibility. Synthetic knowledge cannot be treated as a neutral input into decision-making. Firms must institutionalize governance mechanisms ensuring transparency in the integration of generative outputs, traceability of algorithmically supported decisions, structured human oversight, and alignment with sustainability objectives. Governance thus becomes integral to quality architecture rather than an external compliance requirement.

Regulatory compliance also reshapes competitive dynamics. The ability to embed governance standards within organizational routines may become a source of legitimacy, resilience, and strategic differentiation. Governance capability itself emerges as a dimension of cognitive capital.

These institutional transformations are inseparable from environmental considerations. Generative infrastructures depend on energy-intensive data center architectures (Strubell et al., 2019; Patterson et al., 2021). If governance seeks to rebalance power and accountability in knowledge production, it must also address the material conditions under which synthetic knowledge is sustained. The governance of cognitive capital therefore extends to resource use, energy intensity, and infrastructural sustainability.

In this systemic sense, governance functions as a balancing mechanism for the tensions identified throughout this study: between cognitive efficiency and epistemic autonomy, decentralized access and infrastructural concentration, and digital productivity and environmental sustainability. The European regulatory turn illustrates how public policy can reshape the architecture of cognitive capital and influence the conditions under which knowledge is mobilized and valorized.

The central question is not only who controls cognitive capital, but under what governance and environmental constraints it can be legitimately and sustainably deployed.

9. Environmental Footprint of Synthetic Knowledge: Sustainability as a Structural Constraint

The environmental footprint of synthetic knowledge challenges the narrative of digital dematerialization. Generative systems are often portrayed as weightless cognitive tools, yet their operation depends on energy-intensive data centers, high-performance computing clusters, specialized hardware, and global supply chains. The training and deployment of large language models require substantial electricity consumption and generate measurable carbon emissions (Strubell et al., 2019; Patterson et al., 2021). The later of these two studies also identifies considerable scope for improvement: large but sparsely activated networks can consume less than a tenth of the energy of dense networks without loss of accuracy. It revises, moreover, the most widely cited earlier estimate downward by a large factor, once the actual hardware, data center and proxy task are taken into account (Patterson et al., 2021). Estimates in this area are therefore provisional, which is itself an argument for the reporting requirements both studies propose. Synthetic knowledge is materially embedded in energy systems rather than detached from them.

Environmental implications extend beyond direct electricity use. Assessment must weigh direct effects against indirect ones, among them the influence such systems exert on environmental research, on education and on public understanding (Rillig et al., 2023). From a sustainability transition perspective, technological innovation unfolds within socio-technical systems shaped by infrastructures and resource flows (Geels, 2002; Markard et al., 2012). Generative infrastructures represent an expanding layer within this architecture, intensifying electricity demand and potentially conflicting with decarbonization trajectories.

This creates a structural tension in knowledge-intensive systems. Generative artificial intelligence enhances cognitive efficiency and accelerates information processing, yet efficiency gains at the informational level may coincide with rising aggregate energy demand. Rebound effects are plausible: improved model performance can stimulate broader adoption and further infrastructural expansion. Digital productivity does not automatically reduce material intensity.

The environmental dimension is closely linked to infrastructural concentration. Actors controlling large-scale generative infrastructures also control energy-intensive computational architectures. As cognitive capital centralizes, environmental externalities concentrate within the same nodes. Governance of synthetic knowledge therefore requires not only oversight of epistemic processes but also scrutiny of energy use, carbon intensity, and infrastructural sustainability.

Taxonomies of risks and guidelines for the governance of artificial intelligence are organized around technological, data-related and analytical dimensions among others (Wirtz et al., 2022); material and energy-related risk has so far occupied a marginal position in them. If generative infrastructures become integral to organizational cognition, environmental accountability cannot remain peripheral. Sustainability becomes a structural constraint on the mobilization and commercialization of synthetic knowledge.

Organizational development cannot, in this light, be evaluated solely through productivity gains. It must incorporate environmental performance indicators associated with digital infrastructures, in the spirit of assessment across economic, social and environmental dimensions (Elkington, 1997). Quality, in this expanded understanding, encompasses epistemic robustness, governance integrity, and environmental responsibility as interdependent dimensions.

Synthetic knowledge thus possesses a dual character: it is simultaneously cognitive and energetic. Its informational advantages are inseparable from material and ecological costs. Recognizing this duality is essential for governance frameworks seeking to reconcile efficiency, epistemic autonomy, competitive dynamics, and sustainability.

Read alongside infrastructural concentration and epistemic asymmetry, the environmental dimension confirms that these processes are structurally interdependent. Synthetic knowledge operates within a layered architecture linking computational scale, value redistribution, governance regimes, and material constraints. The analytical task is therefore integrative rather than fragmentary.

10. Synthetic Knowledge as Systemic Capital: Toward an Integrated Framework

The preceding analyses show that generative artificial intelligence is not simply a technological innovation but a reconfiguration of cognitive capital. Synthetic knowledge is generated within concentrated infrastructures, mobilized within organizations, and shaped by governance regimes and environmental constraints that extend beyond firm boundaries. Its production and valorization unfold across infrastructural, organizational, and institutional layers.

To capture these dynamics, synthetic knowledge can be conceptualized as systemic capital. The term is used here in a sense already available within the knowledge-based literature. Spender (1996) observes that systems theory bridges two levels of analysis, the functioning system and its components, and that systemic properties arise from the activities between them. Identical systemic characteristics, he notes, can be produced from components of different kinds. When the component supplying cognition changes from a human specialist to a model, the system may continue to display much the same properties while what produces them has changed entirely. Unlike traditional knowledge capital, which resides in the people and processes of a single organization, systemic cognitive capital is externally generated, infrastructurally mediated, and materially constrained. Its value depends not only on internal capabilities but on the architecture of infrastructures, governance arrangements, and ecological limits within which it operates.

Three interdependent dimensions define this configuration:

- First, infrastructural concentration. Synthetic knowledge is produced within centralized architectures characterized by capital-intensive infrastructures, proprietary datasets, and large-scale computational capacity. Control over these infrastructures shapes access to cognitive resources and structures value distribution.
- Second, epistemic asymmetry. Organizations integrate synthetic outputs into decision-making without governing the conditions of their production. Interpretive authority shifts toward infrastructural platforms, redistributing cognitive power.
- Third, environmental constraint. The production and scaling of synthetic knowledge depend on energy-intensive infrastructures, embedding cognitive capital within material and ecological boundaries. Knowledge creation is inseparable from resource use and sustainability trade-offs.

These dimensions are mutually reinforcing. Concentration amplifies epistemic asymmetry by centralizing control over model development. Asymmetry increases reliance on governance mechanisms designed to ensure transparency and accountability. Governance frameworks increasingly incorporate sustainability criteria, while ecological constraints influence infrastructural investment and scaling strategies. Synthetic knowledge capital thus emerges as a relational system shaped by feedback between technological scale, institutional governance, and ecological limits.

From a management and quality perspective, this configuration requires a strategic shift. Organizational development cannot be reduced to internal capability accumulation. Firms must cultivate epistemic capability while embedding governance standards and sustainability considerations into decision-making. Organizational quality becomes inseparable from responsible participation in infrastructurally concentrated and environmentally constrained systems.

The theoretical contribution of this framework lies in reframing generative artificial intelligence as a reorganization of cognitive capital within a layered socio-technical architecture. Conceptualizing synthetic knowledge as systemic capital integrates management theory, governance scholarship, and sustainability transition research into a unified explanatory model. The analytical focus moves from firm-level knowledge possession to system-level knowledge orchestration under conditions of concentration and ecological constraint.

Reconceptualizing synthetic knowledge in this way also alters its valuation. Unlike traditional intellectual capital, largely detached from material intensity, synthetic knowledge capital is intrinsically tied to computational infrastructures whose scale determines both competitive advantage and environmental burden. Its assessment must incorporate infrastructural dependency and ecological externalities as structural parameters. A balanced development model therefore requires alignment between organizational quality management and sustainability governance.

This integrated framework provides the basis for articulating a formal systemic model of synthetic knowledge capital, specifying the relational architecture linking infrastructural concentration, epistemic asymmetry, organizational quality, governance mechanisms, and environmental constraints.

11. Results of the Conceptual Analysis

The conceptual analysis conducted in this study leads to three key findings: synthetic knowledge is produced within concentrated infrastructures, it generates epistemic asymmetry in organizational use, and it remains materially constrained by environmental externalities. On this basis, the model below translates these three findings into five interdependent layers. Rather than treating infrastructure, epistemic mediation, organizational quality, externalities, and governance as separate variables, the model conceptualizes them as elements of a single architecture, one that produces cognition, redistributes authority, and redefines responsibility.

Layer 1: Infrastructural production. Synthetic knowledge is generated within concentrated computational architectures characterized by large-scale data aggregation, advanced engineering capacity, and energy-intensive infrastructures (Bommasani et al., 2021), where performance follows power-law relationships with model size, data volume and computing resources (Kaplan et al., 2020). This layer establishes the material and economic conditions of cognitive production and scaling.

Layer 2: Epistemic mediation. Organizations integrate model-generated outputs into decision processes without controlling training regimes, optimization logics, or update cycles. The result is epistemic asymmetry: interpretive authority shifts toward infrastructural platforms while generative processes remain partially opaque (Burkhardt, Rieder, 2024).

Layer 3: Organizational integration and quality governance. Synthetic outputs are mobilized in strategy and operations. Organizational quality depends on epistemic capability, supported by validation routines, human oversight, and safeguards for interpretive autonomy (Shrestha et al., 2019; Wirtz et al., 2022). Resilience becomes tied to the governance of the human–algorithm interface.

Layer 4: Systemic externalities. The synthetic knowledge regime generates effects beyond firm boundaries: infrastructural dependency, risks of epistemic homogenization, and environmental costs associated with computational scaling (Strubell et al., 2019; Patterson et al., 2021). These externalities shape competition, sustainability trajectories, and systemic stability.

Layer 5: Regulatory and sustainability governance. Institutional frameworks, including the European Union's Artificial Intelligence Act, seek to rebalance asymmetries through transparency, oversight, and accountability requirements (European Union, 2024; Hulok, 2025;

Graux et al., 2025). Governance reconnects infrastructural production with responsibility, including environmental accountability.

The model is relational rather than sequential. Infrastructural concentration shapes epistemic mediation; asymmetry conditions organizational quality; externalities trigger governance responses; and regulatory interventions influence infrastructural investment and platform design. Synthetic knowledge operates as systemic capital because its production, deployment, and stabilization are distributed across these mutually reinforcing layers.

Compared with traditional intellectual capital, synthetic knowledge differs in three respects: its production is infrastructurally centralized, its use is organizationally distributed yet epistemically mediated, and its valorization generates material and environmental externalities requiring multi-level governance. Cognitive capital thus becomes inseparable from infrastructural concentration, ecological constraint, and institutional regulation.

The model contributes by extending the knowledge-based view to account for infrastructural externalization, formalizing epistemic asymmetry as a governance-relevant variable, and integrating sustainability constraints into the theory of cognitive capital. By shifting attention from generative artificial intelligence as a tool to generative artificial intelligence as an architecture of cognitive capital, it establishes a structured agenda for empirical research on infrastructural dependency, epistemic capability, governance integration, and environmental impact in knowledge-intensive systems.

The model also provides a foundation for future empirical research by identifying key analytical dimensions that can be operationalized and tested across different organizational contexts, including variations in epistemic capability, infrastructural dependency, and governance integration.

12. Discussion: Conceptual Model of Synthetic Knowledge as Systemic Capital

The proposed model extends previous research in three important ways. First, while the knowledge-based view treats the firm as an integrator of knowledge held by identifiable individuals (Grant, 1996), the present study demonstrates its infrastructural externalization. Second, whereas prior research on generative artificial intelligence has focused on automation and augmentation (Raisch, Krakowski, 2021), this article identifies a deeper transformation of cognitive capital. Third, recent studies order the field at the level of challenges to adoption (Strelau, 2025; Cerchione, Liccardo, Passaro, 2026), whereas the present framework addresses what happens to knowledge capital itself once the cognitive resource is produced outside the firm.

These findings also indicate important differences between prior research and the present study. While earlier studies focused primarily on efficiency gains and technological capabilities, the present model highlights structural dependencies, epistemic constraints and environmental externalities. This shift suggests that future research should move beyond firm-level analyses and incorporate system-level perspectives on cognitive capital and governance. Synthetic knowledge should therefore be analyzed not only as a technological phenomenon, but as a structural transformation of cognitive capital embedded in broader socio-technical systems.

Two boundaries of the argument deserve statement. The framework is analytical rather than predictive: it specifies relations among layers without asserting the strength or the direction of any particular effect. The empirical material on which it draws is also uneven, since evidence on energy consumption is more developed than evidence on epistemic dependency inside organizations, and the latter has yet to be measured directly.

13. Summary

13.1. Conclusions

The argument advanced here treats generative artificial intelligence as a structural transformation of cognitive capital rather than as an enhancement of organizational tools. Conceptualizing synthetic knowledge as systemic capital enables management and quality sciences to integrate three interrelated dimensions: infrastructural concentration, epistemic asymmetry, and environmental constraint.

Three conclusions follow, one for each of the research questions posed above:

- First, knowledge production is increasingly externalized. It is generated within concentrated infrastructures and subsequently integrated into organizational processes, challenging the assumption that cognitive capital is primarily cultivated through firm-level routines and internal learning.
- Second, concentration generates epistemic asymmetry. Organizations mobilize synthetic outputs without controlling the architectures that produce them. Competitive advantage shifts from knowledge ownership toward epistemic capability exercised within accountable decision structures.
- Third, cognitive capital is materially grounded. Synthetic knowledge depends on energy-intensive infrastructures and produces environmental externalities. Knowledge is no longer purely informational; it is simultaneously cognitive and energetic, shaped by ecological constraints and regulatory frameworks.

These three arguments support a reconceptualization of knowledge capital as infrastructurally mediated, governance-dependent, and environmentally constrained. The proposed model shifts analytical attention from generative artificial intelligence as a discrete technology to generative artificial intelligence as a system-level architecture of cognitive capital embedded in infrastructural and ecological constraints.

The model contributes on three counts: it carries the knowledge-based view beyond the firm so that externalized production falls within its scope, gives epistemic asymmetry a definite place among the variables that governance has to address, and brings material constraint inside the theory of cognitive capital.

This reconceptualization challenges traditional management perspectives that treat knowledge as an internally governed resource and instead positions cognitive capital within broader infrastructural and ecological systems. As a result, management research must extend its analytical focus beyond firm-level capabilities toward system-level dependencies, governance mechanisms, and sustainability constraints shaping knowledge production.

13.2. Limitations

This study is conceptual and does not rely on primary empirical data. The model therefore requires empirical validation across sectors and organizational forms. Future research should operationalize epistemic capability through measurable indicators capturing how organizations evaluate, contextualize, and govern synthetic outputs in practice. Comparative research across corporations, public institutions and knowledge-intensive small and medium-sized enterprises would clarify variations in governance routines, procurement strategies, audit practices, and sustainability reporting linked to foundation model integration.

Further empirical work should examine infrastructural dependency, including contractual lock-in, switching costs, and value capture between organizations and infrastructure providers. Although environmental externalities are documented in existing literature, this study does not quantify the impacts of generative infrastructures. Interdisciplinary research combining management studies with energy systems analysis and environmental economics is needed to assess carbon intensity, energy transparency, and rebound effects more precisely.

Future empirical research may operationalize epistemic asymmetry through indicators such as transparency of model documentation, access to information about training data, the organization's ability to audit or contest outputs, dependence on a limited number of providers, contractual restrictions on model use, switching costs, and the existence of internal validation routines. These indicators build on features the literature already identifies: the bearing of release practice on what can be inspected (Bommasani et al., 2024), the mediating role of platform architectures (Burkhardt, Rieder, 2024), and unequal epistemic agency among those who depend on such systems (Olaniyan, Martins, Al Maqrashi, 2026). Together they would allow future studies to move from conceptual diagnosis toward measurable assessment of epistemic dependency in organizations using generative artificial intelligence.

Given the rapid evolution of generative technologies and regulatory regimes, the model should be treated as provisional and open to refinement as architectures, market structures, and sustainability constraints evolve. Even so, it offers a structured foundation for future research at the intersection of organizational quality, infrastructural governance, and sustainability transformation, and invites a rethinking of cognitive capital under conditions of systemic technological dependence.

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