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Centralization of artificial intelligence infrastructure and technological autonomy in the Global South.

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A centralização da infraestrutura de inteligência artificial (IA) representa um desafio estratégico para empresas do Sul Global, pois compromete sua soberania digital, competitividade econômica e segurança geopolítica. A concentração de dados e poder computacional em um pequeno número de provedores globais de tecnologia, cujas sedes e origens tecnológicas estão enraizadas em economias avançadas, limita a inovação local, dificulta o desenvolvimento de ecossistemas tecnológicos autônomos e expõe esses países à dependência estrutural de infraestruturas estrangeiras. Esta pesquisa visa compreender as implicações dessa centralização, com foco em como ela afeta a autonomia tecnológica e o posicionamento estratégico de empresas do Sul Global, examinando as dimensões estruturais, econômicas e geopolíticas por meio das quais essa dependência se manifesta e remodela os ecossistemas tecnológicos locais. A metodologia é qualitativa, baseada em entrevistas semi estruturadas com executivos seniores responsáveis por tecnologia e estratégia digital em empresas consolidadas fundadas no Sul Global, buscando investigar como a centralização da infraestrutura de IA afeta a autonomia tecnológica de empresas em economias emergentes. Como contribuição prática, esta pesquisa propõe um arcabouço teórico para apoiar a formulação de estratégias de negócios voltadas para a construção de ecossistemas de IA mais resilientes, contribuindo para mitigar a exposição de países emergentes à “colonização digital” e fortalecer sua posição na economia digital global.

Palavras-Chave: inteligência artificial, infraestrutura digital, dados, tecnologia centralizada, economia, microeconomia, mercados emergentes

Abstract

The centralization of artificial intelligence (AI) infrastructure presents a strategic challenge for companies in the Global South, as it compromises their digital sovereignty, economic competitiveness, and geopolitical security. The concentration of data and computational power in a handful of global technology providers whose headquarters and technological origins are rooted in advanced economies limits local innovation, hinders the development of autonomous technological ecosystems, and exposes these countries to structural dependency on foreign infrastructures. This research aims to understand the implications of such centralization, focusing on how it affects the technological autonomy and strategic positioning of companies in the Global South, examining the structural, economic, and geopolitical dimensions through which this dependency manifests itself and reshapes local technological ecosystems. The methodology is qualitative, based on semi-structured interviews with senior executives responsible for technology and digital strategy in well-established companies founded in the Global South, seeking to investigate how AI infrastructure centralization affects the technological autonomy of companies in emerging economies. As a practical contribution, this research proposes a theoretical framework to support the formulation of business strategies aimed at building more resilient AI ecosystems, contributing to mitigate the exposure of emerging countries to “digital colonization” and strengthen their position in the global digital economy.

Key words: artificial intelligence, digital infrastructure, data, centralized technology, economy, microeconomics, emerging markets

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Summary

1 Introduction

Artificial Intelligence (AI) has established itself as one of the primary drivers of the contemporary global economy, fostering innovation, enhancing efficiency, and redefining competitive dynamics across multiple strategic sectors (Crawford, 2021; Van Der Vlist et al., 2024). More than an economic vector, AI has begun to restructure international power relations, consolidating a new informational geopolitics marked by asymmetries in access to and control over digital infrastructure (Ferrari et al., 2023; Khanal et al., 2024). This infrastructure, encompassing data centers, cloud computing platforms, storage systems, and the capacity to train advanced models such as Large Language Models (LLMs), is highly concentrated in a small number of technology corporations predominantly headquartered in the United States (Ahmed et al., 2023).

Large global technology corporations, although originating primarily from developed economies, especially the United States, not only provide digital infrastructure and AI-based solutions but also exert increasing influence over political, economic, and social decision-making on a global scale (Van Der Vlist et al., 2024). This dynamic reveals an architecture of technical interdependence that masks deeper relationships of economic and geopolitical dominance. When countries lack control over their own AI infrastructure, including computational capacity, data pipelines, and cloud environments, they become structurally dependent on decisions made by foreign public and private actors. Such dependence restricts their ability to develop autonomous technological capabilities, limits local innovation, and reinforces asymmetric power relations in the global digital economy (Ferrari et al., 2023).

The phenomenon known as “Big AI” encapsulates this concentration of power. It refers to the dominance of a handful of corporations that possess unparalleled computational resources, vast proprietary datasets, specialized technical talent, and control over global AI distribution and governance pipelines (Birhane, 2023; Bender et al., 2021). These actors effectively determine innovation trajectories, influence regulatory frameworks, and set infrastructural and ethical standards that ripple across the world. As a result, companies and states in the Global South face significant structural barriers to building autonomous AI ecosystems, becoming dependent on external infrastructures and governance mechanisms that they do not control (Kalluri, 2020).

For large firms in the Global South, this infrastructural asymmetry produces substantive constraints because it restricts their capacity to govern the technological substratum that enables advanced AI development. Lacking sovereign control over large-scale computational resources, proprietary data pipelines, and model-governance frameworks, these companies become structurally dependent on foreign providers to store, process, and operationalize strategic data. Such dependency limits their ability to customize models to region-specific linguistic, cultural, and socio-economic contexts, thereby increasing the likelihood of biased inferences, reduced model accuracy, and decisions misaligned with local market dynamics (Couldry and Mejias, 2019; Mann and Daly, 2019; Abebe et al., 2022). As a result, the centralization of AI infrastructure not only narrows the strategic autonomy of these firms but also reinforces long-standing structural inequalities, heightening their economic vulnerability and geopolitical exposure within global digital value chains (Luitse and Denkena, 2021; Khanal et al., 2024; Zhang et al., 2023).

The increasing politicization of digital infrastructure further complicates this scenario. Public policies adopted by certain governments, particularly in contexts of strategic competition, indicate that the growing influence of large private technology corporations over data flows, algorithms, and digital platforms can extend beyond the economic sphere to affect electoral processes and political communication practices. By shaping digital environments, these corporations influence public discourse, contribute to the establishment of technological standards, and participate in the formulation of guidelines for AI implementation, including within academic and research institutions. This process tends to reinforce a technocratic approach to technological development, often guided by perspectives and interests rooted in the Global North, which may pose challenges to the scientific and cultural autonomy of developing countries (Luchs and Apprich, 2023).

The transformation of AI infrastructure into a strategic asset has revealed systemic risks associated with technological concentration and dependence. Nations lacking control over their digital infrastructure are more susceptible to technological disruptions resulting from political decisions or external economic interests (DeNardis, 2020; Schmitt, 2020). This vulnerability underscores the importance of digital sovereignty as a critical component of national resilience in an increasingly data-driven global context (Smith et al., 2022; Baldoni and Di Luna, 2025;

Richardson et al., 2025). Moreover, the political implications of dependence on foreign technological infrastructure reveal deeper tensions between global competitiveness and national autonomy (Pohle and Thiel, 2023).

Moreover, AI centralization amplifies preexisting disparities. Emerging markets face barriers to accessing high-performance infrastructure, undermining their capacity to compete in critical sectors such as healthcare, education, and finance (Crawford, 2021; Luchs and Apprich, 2023). Dependence on foreign platforms also exposes these economies to unfair practices such as data monopolization and algorithmic manipulation, negatively affecting equity, transparency, and informational sovereignty (Benjamin, 2019; Eubanks, 2018; Mohamed et al., 2020; Luitse and Denkena, 2021).

Amid the growing centralization of artificial intelligence (AI) infrastructure, companies in the Global South face increasing challenges to their digital sovereignty and technological autonomy. While existing literature has explored the economic and geopolitical implications of AI dependence, there remains a gap in understanding how this centralization concretely affects the strategic and technological positioning of companies operating in emerging economies. From a cost-based theoretical perspective, this dependence can be interpreted as generating structural costs, such as high switching costs, lock-in effects, and reduced bargaining power, that constrain the capacity of firms to autonomously develop, adapt, and scale AI solutions. In light of this scenario, this study addresses the following research question: how does the centralization of AI infrastructure and models by major technology corporations reconfigure global power relations and shape the economic, technological, and strategic autonomy of the Global South? The analysis therefore draws on theoretical approaches that conceptualize digital dependence as a form of cost asymmetry, emphasizing how the concentration of AI infrastructure affects the strategic alternatives, innovation capacity, and long-term competitiveness of large firms in emerging markets (Lim et al., 2022; Salama et al., 2023).

This article seeks to propose a framework that addresses the research question by representing how the centralization of AI infrastructure reconfigures technological autonomy in the Global South. The theoretical contribution lies in advancing the understanding of digital dependence as a multidimensional phenomenon that combines technical, economic, and geopolitical factors (Floridi, 2021; Taylor, 2023). The practical contribution focuses on informing business strategies and public policies aimed at fostering more resilient, equitable, and autonomous AI ecosystems (Ferrari et al., 2023; Van Der Vlist et al., 2025; Aziz and Telmom, 2023).

2 Development

2.1 Theoretical Background

To analyze the centralization of artificial intelligence (AI) infrastructure and its impacts on the digital sovereignty of emerging countries, this study adopts cost theory as its main analytical lens. This perspective makes it possible to understand how decisions related to the control, access, and use of digital infrastructure translate into economic, strategic, and institutional costs for companies in the Global South. By framing AI centralization not only as a technological phenomenon but also as a structure that imposes transaction costs, opportunity costs, and strategic dependency costs, the analysis explores how the concentration of data, computational capacity, and algorithmic models affects technological autonomy and the competitive positioning of emerging economies. Therefore, cost theory provides a conceptual framework for assessing the economic and geopolitical externalities of centralization and for supporting strategies aimed at building more resilient and decentralized AI ecosystems.

2.1.1 Artificial Intelligence Infrastructures

Artificial intelligence (AI), as a structuring technology of the contemporary digital economy, depends on a complex material base for its operation. This base, composed of physical, digital, and institutional resources, constitutes what is commonly referred to as AI infrastructure. Far from operating in a technical vacuum, AI systems are deeply anchored in high-performance devices, data storage and processing networks, computational platforms, and specialized organizational structures that enable the large-scale development, training, and application of algorithmic models (Crawford, 2021; Ahmed et al., 2023; Ferrari et al., 2023).

At the core of this infrastructure are data centers, responsible for the massive storage and processing of information. These environments require high investments, abundant energy, and sophisticated management to ensure high standards of performance, security, and availability (Smith et al., 2022).

Complementing these are cloud computing platforms, which provide remote and scalable access to critical computational resources for algorithmic intelligence tasks (Van Der Vlist et al., 2024).

Another essential component is specialized hardware, such as graphics processing units (GPUs) and chips specifically designed for deep learning. These devices are indispensable for training complex neural networks, such as large-scale foundational models (Zhang et al., 2023; Ahmed et al., 2023). However, access to such hardware is conditioned by global production chains that are often opaque and subject to geopolitical interests, which restricts the digital sovereignty of countries lacking control over these technologies (Luchs and Apprich, 2023).

Furthermore, the effectiveness of artificial intelligence models is directly tied to the availability, quality, and diversity of the data used during training. Leveraging such data responsibly requires robust data storage and governance systems that can ensure privacy, security, and ethical integrity, particularly when dealing with sensitive or publicly relevant information. However, access to these resources is often concentrated in large corporations or technological hubs in developed countries, which control not only vast datasets but also the infrastructure and training pipelines needed to build state-of-the-art models. This monopolization of intangible assets exacerbates technological and economic inequalities, reinforcing asymmetries between technology-producing centers and peripheral users, who remain dependent on externally developed solutions and lack the autonomy to drive local innovation (Lim et al., 2022; Salama et al., 2023; Ferrari et al., 2023; Luitse and Denkena, 2021; Couldry and Mejias, 2019).

AI infrastructure also encompasses algorithmic development environments, such as machine learning frameworks and libraries. Although many of these resources are made available as open-source, their development and updating remain under the control of a limited number of institutions and developers, mostly based in Global North countries (Ahmed et al., 2023; Van Der Vlist et al., 2024). This establishes a form of technical centralization that directly influences the directions of innovation and the possibilities of customizing AI to local realities (Luchs and Apprich, 2023).

Recent research has highlighted the importance of understanding this infrastructure as a sociotechnical and geopolitical phenomenon. Crawford (2021), in analyzing the political ecology of AI, proposes a systemic reading of the technology as a global arrangement of extraction, processing, and decision-making. Ferrari et al. (2023) argue that AI should not be treated merely as a set of tools but as a critical infrastructure that organizes power relations and access to knowledge. Ahmed et al. (2023) reinforce this point by demonstrating that advances in applied AI are deeply linked to the control of strategic infrastructural assets such as computational clusters, data repositories, and cloud infrastructure.

Taking AI infrastructure as a central object of analysis helps denaturalize the dynamics that sustain algorithmic production and reveals the mechanisms of exclusion and dependency that shape the contemporary digital ecosystem. The ability to actively participate in the development of AI solutions depends not only on human talent or research incentives but also, and above all, on access to this infrastructural base, which is distributed in an unequal manner (Smith et al., 2022; Khanal et al., 2024).

This approach makes it possible to question narratives of technological neutrality and to understand how technical decisions made in specific environments affect the economic and informational sovereignty of entire countries. AI infrastructure, therefore, is not a neutral backdrop but a strategic field of dispute, where the contours of emerging countries' inclusion, or exclusion, in the global digital economy are defined (Crawford, 2021; Van Der Vlist et al., 2025).

In this scenario, debates and initiatives aimed at decentralizing control over data have gained relevance. Although much of the technological platforms and infrastructure providers operate under highly centralized models, in which vast data banks are concentrated within proprietary architectures operated by a limited number of actors, alternatives are emerging that seek to redistribute control over information flows and promote more democratic models of data governance (Taylor and Purtova, 2021).

Experiments with data commons and data trusts propose collective structures for managing and sharing data, in which communities, civil society organizations, and public institutions actively participate in defining the rules for data use, access, and redistribution (Pentland, 2021).

Moreover, technical approaches such as federated learning allow AI models to be trained across multiple decentralized sources without the need to transfer data to centralized repositories, mitigating privacy risks and promoting greater local autonomy over informational assets (Kairouz et al., 2021). International initiatives for building data cooperatives, federated architectures, and interoperable infrastructures reinforce this movement, although technical and economic centralization remains a significant challenge to constructing a more equitable and distributed AI ecosystem (Delacroix and Lawrence, 2019; Crawford, 2021; Ferrari et al., 2023).

Artificial intelligence, often treated as an applied technology, must be understood as an integral part of the critical infrastructure that sustains the contemporary digital economy (Crawford, 2021; Ferrari et al., 2023). Just as roads, electrical grids, and telecommunications systems played central roles in industrialization and modernization processes during the twentieth century, AI has become part of the material, symbolic, and geopolitical foundations of the digital age (Smith et al., 2022; Khanal et al., 2024).

This infrastructural condition of AI goes beyond code and algorithms. It refers to a complex sociotechnical architecture composed of high-performance supercomputers, global networks of data centers, cloud computing platforms, cross-border data flows, and technical standards embedded in libraries and frameworks controlled by a few dominant actors (Ahmed et al., 2023; Luchs and Apprich, 2023). Kate Crawford (2021) characterizes this global mesh as a political, economic, and ecological system, whose operation relies on intensive mineral extraction, distributed labor exploitation, and technical decisions with far-reaching ethical, environmental, and geopolitical consequences.

The concentration of this infrastructure in a small number of transnational corporations, mostly headquartered in the United States and China, has produced what authors such as Ferrari et al. (2023) and Van Der Vlist et al. (2024) describe as a new structural asymmetry of digital capitalism. Ahmed et al. (2023) show that the main centers of applied AI research, as well as cutting-edge computational resources, are increasingly under private control, raising significant barriers to entry for new actors, especially those from developing countries.

This scenario supports the argument that we live under a regime of "infrastructural dependency" (Van Der Vlist et al., 2024), in which the exercise of digital sovereignty depends on access, often mediated by foreign interests, to the technical elements essential for training, operating, and updating artificial intelligence models. The geopolitics of AI must therefore be analyzed not only in terms of its strategic use, but also in relation to the control of its material components: from servers to bandwidth, from data to specialized chips, from technical standards to computational energy (Salama et al., 2023; Lim et al., 2022).

In emerging markets, this dependency becomes even more acute. The lack of local infrastructure capable of supporting high-complexity AI models compels companies and public institutions to rely on external providers. This situation not only undermines technological autonomy, but also exposes sensitive data to risks of interception, manipulation, or misuse (Zhang et al., 2023; Luitse and Denkena, 2021). Such dynamics reinforce the peripheral status of these countries within the global innovation system and consolidate a new form of digital colonialism (Crawford, 2021; Luchs and Apprich, 2023).

The growing global race for computational power, access to data, and control over digital infrastructures reveals that AI has surpassed its status as a mere tool and now operates as a structuring force of economic and political power. The ability to develop proprietary models, define technological standards, and maintain autonomous AI ecosystems has become a strategic advantage in global competition (Ferrari et al., 2023; Ahmed et al., 2023).

Thus, analyzing AI as strategic infrastructure pushes the debate beyond the realm of technological innovation and into the domains of international political economy, national security, and institutional development architecture (Van Der Vlist et al., 2025; Smith et al., 2022). Understanding this dimension is essential for designing institutional responses, public policies, and corporate strategies that reduce digital vulnerability in peripheral countries and enable more equitable models of integration into the global digital economy.

2.1.2 Centralization of AI Infrastructure

Artificial intelligence, consolidated as a central element of the global digital infrastructure, is advancing in parallel with a process of technical, economic, and epistemic centralization (Crawford, 2021; Ferrari et al., 2023). Rather than fostering a plural environment for innovation, its infrastructure has followed logics of extreme concentration. Data, computational power, and operational protocols are under the control of a small number of agents with transnational coordination capacity (Ahmed et al., 2023; Van der Vlist et al., 2024).

This phenomenon, often described as “Big AI”, signals a new stage of informational capitalism. In this configuration, large volumes of data, proprietary computational architectures, and closed ecosystems converge to consolidate global asymmetries. AI, under such an arrangement, becomes an instrument of power, capable of restricting access to technical knowledge, limiting collective self-determination, and directly influencing the trajectory of scientific development (Zhang et al., 2023; Khanal et al., 2024).

Ferrari et al. (2023) observe that this fusion between infrastructure and market transforms AI into a silent mechanism of governance. Technical decisions embedded in algorithmic systems shape entire sectors of social life. The resulting hegemony goes beyond computation: it involves institutions, regulations, and decision-making dynamics. Controlling the operating systems of AI ultimately means defining what will be known, predicted, and decided.

This hegemony is also sustained by the capture of regulatory processes. Khanal et al. (2024) demonstrate that concentrated infrastructure allows major corporations to directly influence technical standards and public policies. This interference destabilizes regulatory neutrality and weakens the ability of States to formulate guidelines aligned with their own strategic interests (Salama et al., 2023).

In the field of knowledge, Luchs and Apprich (2023) describe the consolidation of a technopedagogical regime focused on scalability, predictability, and measurability. This model tends to reproduce hegemonic knowledge patterns, overlooking sociocultural diversity and devaluing local knowledge. Automated learning systems, when shaped by centralized infrastructures, reinforce a logic that universalizes solutions and marginalizes contexts.

Van der Vlist et al. (2024) deepen this discussion by pointing out that control over the infrastructural layer of AI creates a grammar of the possible. Technological solutions aligned with the interests of major platforms gain legitimacy and visibility. Other proposals, rooted in peripheral realities or critical of the dominant logic, are overlooked or dismissed (Ahmed et al., 2023).

This pattern of concentration directly affects the autonomy of countries with limited technological capacity. Without local means to store, process, and train advanced models, these regions remain dependent, not only in technical terms, but also in relation to the logics that shape algorithmic production (Luitse and Denkena, 2021). Such dependency weakens scientific institutions, undermines informational sovereignty, and perpetuates new forms of digital subordination (Crawford, 2021).

The centralization of AI infrastructure, therefore, reorganizes the global conditions for the production of knowledge and innovation. Its effects go beyond the technical dimension, reaching the political, economic, and epistemic spheres in a structural way (Ferrari et al., 2023; van der Vlist et al., 2025). Confronting this logic requires more than decentralized technological solutions: it demands new institutional agreements and a critical repositioning toward the structures that underpin contemporary AI.

2.1.3 Digital Sovereignty and Technological Autonomy in Emerging Countries

The transformation of artificial intelligence into critical infrastructure has profound implications for the digital sovereignty of countries that do not hold direct control over the technical and institutional means that sustain this technology. In particular, nations classified as emerging face a condition of structural vulnerability, marked by dependence on external computational resources, normative subordination to global technical-legal standards, and asymmetry in access to strategic information. In this context, digital sovereignty ceases to be a conceptual abstraction and becomes a concrete dimension of the exercise of political, economic, and epistemological autonomy. (Smith et al., 2022)

This condition of dependency is not limited to the use of imported technological solutions. It reflects a systemic configuration in which the entire AI cycle, from data collection to processing, from model training to deployment in applications, is mediated by infrastructures beyond the regulatory and technical reach of peripheral countries. The inability to control or audit such systems compromises not only the confidentiality and security of data, but also the capacity to formulate evidence-based public policies and to promote endogenous innovation.

Smith et al. (2022) warn of the geopolitical risks associated with this form of digital dependence. By outsourcing critical functions to platforms operated by third parties, developing countries become exposed to technological discontinuities, service interruptions, and restrictions in defining their own digital agendas. This scenario is further aggravated by the increasing politicization of data flows and the instrumentalization of algorithmic infrastructure as a tool of transnational influence.

In the domains of knowledge production and cultural representation, the impacts of this dependency become even more evident. Luitse and Denkena (2021), in their analysis of the role of large-scale language models in shaping social life, show that AI systems trained on datasets predominantly from the Global North tend to reproduce hegemonic worldviews, obscuring local contexts, erasing marginal identities, and reinforcing colonial hierarchies. The automatic reproduction of these biases does not stem from malicious algorithmic intent, but from the very data architecture that underpins such systems, an architecture that reflects and amplifies historical structures of exclusion.

Global South authors such as Diego Vicentin, Sérgio Amadeu, and Danilo Doneda contribute to the conceptualization of “data colonialism”, in which the massive extraction and remote processing of information from peripheral countries reinforces logics of informational subordination. This process digitally mirrors patterns of exploitation and dependency already observed in previous cycles of the global economy. In this sense, contemporary algorithmic infrastructure not only sustains business models but also rearticulates center-periphery relations in the realms of knowledge and governance.

The microeconomics of infrastructure, in turn, reveals the scale of the challenge. Building autonomous technological capacity requires significant investments in data centers, connectivity networks, high-performance equipment, specialized workforce training, and robust legal frameworks to ensure interoperability, security, and transparency. Without coordinated public policies and a long-term strategic vision, emerging countries tend to remain in the position of consumers of ready-made solutions, without access to the mechanisms that define the rules of the technological game.

2.1.4 Global Governance of AI Infrastructure

The centralization of artificial intelligence (AI) infrastructure does not occur in a regulatory vacuum. On the contrary, its consolidation as a global strategic asset also reflects the absence of robust international frameworks to regulate access to, use of, and interoperability of digital infrastructure. Unlike sectors historically subjected to multilateral regimes, such as telecommunications (ITU) or civil aviation (ICAO), AI has evolved within a fragmented institutional landscape, dominated by private agreements, proprietary technical standards, and a lack of global public governance (Taylor and Purtova, 2021; Ferrari et al., 2023).

This regulatory gap fosters a dynamic of “de facto norms”, in which a small number of transnational corporations establish practices that become hegemonic on a global scale. Control over APIs, machine learning frameworks, interoperability protocols, and data architecture grants these actors disproportionate influence over the technical and political evolution of AI (Benkler, 2022; Ahmed et al., 2023). As Crawford (2021) observes, AI today acts as a vector of private governance, operating under market logics that often conflict with democratic values, fundamental rights, and sustainable development goals.

This fragmented governance has direct implications for emerging countries. Without a multilateral regime ensuring equitable access to infrastructural resources, interoperable standards, and transparency in data flows, these nations remain structurally dependent (Ferrari et al., 2023; Khanal et al., 2024). The imposition of technical standards created in foreign contexts further marginalizes local solutions and hampers the development of technological ecosystems compatible with the needs and values of each society (Luchs and Apprich, 2023).

Moreover, the absence of global governance mechanisms hinders progress on fundamental principles for ethical and sustainable AI, such as algorithmic justice, environmental protection, and respect for cultural diversity (Taylor and Purtova, 2021). Regional initiatives and international consortia have sought to address this gap, but they still lack normative strength and enforcement mechanisms to ensure effective inclusion of the interests of the Global South (Benkler, 2022).

In this context, building a global governance regime for AI infrastructure becomes imperative. It is not merely a matter of regulating algorithms but of establishing principles, rights, and responsibilities to guide the development, distribution, and use of digital infrastructures on a planetary scale. Digital sovereignty, understood as the capacity of countries and communities to shape their own technological ecosystems, depends, to a great extent, on the construction of fair and transparent global rules (Ferrari et al., 2023; van der Vlist et al., 2025). Without such governance, AI infrastructure will continue to reproduce and intensify the geopolitical and economic asymmetries of the international system.

2.1.5 Environmental and Energy Impacts of AI Infrastructure

The accelerated expansion of artificial intelligence (AI) infrastructure brings to light a dimension often overlooked in debates about technological centralization: the environmental and energy impacts associated with operating and training large-scale algorithmic models. The transformation of AI into a global strategic asset entails increasing consumption of natural resources, with direct effects on sustainability dynamics, environmental justice, and climate justice (Crawford, 2021; Zhang et al., 2023).

Training large models, such as Large Language Models (LLMs), consumes vast amounts of electricity and requires an intensive physical infrastructure composed of high-performance data centers and global connectivity networks (Strubell et al., 2019; Smith et al., 2022). These data centers, in turn, depend on a constant and massive electricity supply and on cooling systems that exacerbate the water footprint of their operations. Studies indicate that training a single large-scale language model can generate carbon emissions equivalent to hundreds of intercontinental flights (Strubell et al., 2019).

Beyond energy consumption, AI infrastructure is linked to global supply chains involving the extraction of rare minerals such as cobalt, lithium, and rare earth elements, which are essential for manufacturing specialized chips and server components (Crawford, 2021; Zhang et al., 2023). The intensive extraction of these resources generates significant socio-environmental impacts, particularly in emerging countries, where poorly regulated extractive practices exacerbate social inequalities and harm local ecosystems (Salama et al., 2023).

The centralization of AI infrastructure tends to exacerbate these impacts by concentrating energy consumption and mineral extraction in certain global hubs. The lack of transparency in the sustainability reporting of large corporations hampers accurate assessment of these effects and limits the ability of emerging countries to influence international standards for environmental responsibility in the digital sector (Ferrari et al., 2023; Lim et al., 2022).

Furthermore, the current model of AI expansion reinforces unsustainable development patterns at the microeconomic level. The widespread adoption of centralized and energy-intensive AI systems places increasing pressure on local energy grids, raises operational costs for small and medium-sized enterprises (SMEs), and limits accessibility for actors lacking robust digital infrastructure. In regions with weaker electrical systems, common in many Global South countries, this creates significant entry barriers for local businesses and public institutions, deepening existing inequalities in technological adoption and innovation capacity (Smith et al., 2022; Khanal et al., 2024). As a result, the growing dependency on high-energy AI solutions risks undermining local energy resilience and compromises the viability of inclusive, sustainable digital development.

In this scenario, ensuring the sustainability of AI infrastructure requires more than incremental energy efficiency. It is necessary to question the premises of unlimited growth in computational power and to promote decentralized, efficient, and environmentally responsible models, such as edge computing and federated learning

(Lim et al., 2022). Incorporating principles of environmental justice into the governance of digital infrastructure is an essential step to ensure that AI not only avoids reproducing but actively contributes to overcoming the socio-environmental inequalities that characterize the contemporary digital economy (Crawford, 2021; Ferrari et al., 2023).

2.1.6 Cost Theory and Infrastructural Dependence

To analyze infrastructural dependence from an economic perspective, this study draws on cost theory, particularly the foundations of transaction cost economics and the literature on switching costs and lock-in. Transaction costs refer to the costs involved in initiating, monitoring, and enforcing exchanges between firms and their infrastructure providers. Classical works define transaction costs as the expenses associated with negotiating, contracting, coordinating, and adapting to external actors (Coase, 1937; Williamson, 1985, 1996). In the context of AI infrastructure, these costs include negotiating service-level agreements, complying with provider-imposed standards, adapting internal architectures to proprietary interfaces, and monitoring unilateral changes to contractual or technical conditions. Opportunity costs denote the value of alternative strategic paths that an organization forgoes when committing to a particular infrastructural arrangement (Knight, 1921; Arrow and Debreu, 1954), such as investing in internal capabilities or diversifying providers rather than concentrating workloads within a single hyperscaler ecosystem.

Switching costs are the financial, technical, and organizational costs incurred when migrating from one provider or technological architecture to another. These costs include direct expenditures,data migration, system reintegration, contract termination fees as well as indirect organizational burdens such as retraining teams, reconfiguring applications, and renegotiating commercial agreements (Farrell and Shapiro, 1988; Klemperer, 1995). When switching costs become sufficiently high, organizations enter a condition of lock-in, in which dependence on a dominant provider constrains strategic flexibility and weakens bargaining power. Lock-in dynamics are especially significant in digital infrastructures because network effects, proprietary ecosystems, and path-dependent learning processes make withdrawal progressively more costly (David, 1985; Arthur, 1989).

From this perspective, AI infrastructure centralization creates a configuration of costs that systematically favors incumbent providers and restricts the autonomy of firms in emerging economies. Centralization raises transaction costs related to oversight and contracting, increases switching costs due to proprietary services and architectural dependencies, and amplifies opportunity costs by reducing the range of viable strategic alternatives. Digital dependence thus emerges not simply as a technological phenomenon but as a form of cost asymmetry, in which the distribution of transaction, switching, and opportunity costs disproportionately burdens dependent firms while concentrating power in global providers (Taylor and Purtova, 2021; Ferrari et al., 2023).

2.2 Methodology

This research adopts a qualitative approach aimed at developing an in-depth understanding of the relationship between the centralization of artificial intelligence (AI) infrastructure and the technological autonomy of companies located in emerging countries (Eisenhardt, 1989).

2.2.1 Research Strategy

The research follows an approach for theory building from multiple case studies, using an iterative process between empirical data and existing literature. This methodology stands out for its flexibility in data collection and analysis, allowing for the refinement of conceptual categories and the generation of robust theoretical insights based on empirical evidence. In this study, the strategy will be applied to identify recurring patterns and contrasts among the perspectives of the interviewed experts (Eisenhardt, 1989).

Additionally, the investigation will be conducted through a multiple case study design, with the goal of examining a contemporary phenomenon embedded in its real-life context. This approach is particularly suitable when the boundaries between the phenomenon and its context are not clearly defined, as is the case with technological infrastructure dependency among companies located in emerging markets (Yin, 2015).

2.2.2 Case and Participant Selection

Participants will be selected through purposive sampling, as recommended in qualitative research, to gather diverse perspectives on how AI infrastructure centralization shapes decision-making and organizational dynamics in well-established companies founded in the Global South (Godoy, 2006; Patton, 2002). The study will focus on senior professionals directly involved in strategic decision-making processes regarding the use, development, or provision of AI solutions and digital infrastructure within these companies. These participants are considered primary sources of evidence due to their direct involvement in the organizational processes under investigation (Eisenhardt, 1989; Yin, 2015).

Company	**Position**	**Industry Sector**
A	Director of Data	Financial Services
B	Director of Technology	Financial Services
C	Director of Technology Infrastructure	Food Delivery
D	Director of Data	Healthcare
E	Director of Technology	Payments
F	Director of Technology	E-Commerce

Table 1 – Interviewees Profile

A total of six semi-structured interviews were conducted, encompassing a diversity of geographical locations, industry sectors, and levels of digital maturity. The selection prioritized professionals based in Brazil, where technological dependence tends to be more pronounced, and included organizations whose technology directors had adopted, at least partially, decentralized solutions such as edge computing, blockchain, and federated learning (Eisenhardt, 1989; Yin, 2015).

In addition to interviews, secondary data were used to complement and enrich the analysis. These data included academic publications on digital sovereignty and AI geopolitics, technical reports published by international organizations, and market analyses from consulting firms such as McKinsey on AI infrastructure and cloud dependence. Contributions from economists and experts in technological geopolitics were also incorporated, enabling a robust methodological triangulation (Gibbons et al., 1994; Yin, 2015).

This combination of primary and secondary sources follows methodological recommendations on source triangulation, enhancing the validity of the findings and allowing for a more comprehensive and contextualized understanding of the studied problem (Yin, 2015).

2.2.3 Data Collection: Semi-Structured Interviews

The primary data collection technique was the semi-structured interview, which allowed the researcher to guide the conversation using a predefined script while adapting to the interviewees' responses and exploring emerging relevant topics throughout the dialogue (Merriam and Tisdell, 2015; Patton, 2002). The interview script was informed by the theoretical framework and divided into thematic blocks: (i) perceptions of AI infrastructure centralization; (ii) effects on technological autonomy; (iii) local mitigation strategies; and (iv) evaluation of decentralized technologies (Eisenhardt, 1989; Yin, 2015).

The interviews were conducted via video conferencing or in person, recorded with the participants' consent, and later transcribed for analysis (Godoy, 2006). Public documents, technical reports, and articles produced by the participants were also used as complementary sources to enhance data triangulation (Gibbons et al., 1994; Yin, 2015).

2.2.4 Data Analysis Procedures

To deepen the understanding of the collected data, the analysis followed established qualitative research procedures, including the systematic reading of interview transcripts, the coding of relevant excerpts, the organization of codes into thematic categories, and the articulation of these categories with the theoretical literature (Merriam and Tisdell, 2015). The analytical process was conducted iteratively, moving back and forth between empirical evidence and conceptual constructs to refine interpretations and strengthen the theoretical alignment of the findings. This iterative approach allows for both the reassessment of previously formulated propositions and the emergence of new insights grounded in practice. The constant comparison technique was employed to ensure analytical consistency and support the development of robust contributions to the discussion on digital sovereignty (Eisenhardt, 1989).

2.2.5 Validation, Reliability, and Ethics

To ensure validity and reliability, the study will adopt strategies such as data source triangulation, peer debriefing, and the involvement of external reviewers in the categorization and interpretation processes. The traceability of analytical decisions will be maintained through a reflective field journal and the systematic documentation of all methodological procedures, ensuring transparency and auditability throughout the research process (Godoy, 2006; Eisenhardt, 1989).

The study will follow ethical principles applicable to research involving human participants, including informed consent, confidentiality, and the responsible handling of shared information (Patton, 2002).

2.3 Results

The interviews revealed a recurring perception among executives regarding the strategic dependence on large technology corporations for sustaining their critical operations and, increasingly, for the development and application of artificial intelligence models. One of the interviewees emphasized this by stating: “Our infrastructure is primarily based on AWS […] the critical point is to avoid vendor lock-in in strategic areas” (Interviewee A). This statement echoes the arguments of Ferrari et al. (2023) and Van der Vlist et al. (2024), who assert that the concentration of computational resources and data in a few global actors generates structural asymmetries that constrain innovation capacity and technological autonomy in the Global South. Furthermore, the testimonies reinforce that dependency is not only technical but also strategically embedded in organizational decision-making, thereby directly linking the empirical evidence to the research question by illustrating how the infrastructural power of Big Tech materially shapes firms’ strategic trajectories.

From an economic perspective, the interviewees reported direct financial impacts stemming from this dependence, such as unilateral changes in pricing and service policies by Big Tech companies. As noted by one participant: “AWS pricing changes happen frequently […] at our scale, this has a significant financial impact” (Interviewee B). This finding aligns with the cost theory perspective adopted in this study as an analytical lens, illustrating how infrastructure centralization imposes transaction costs, opportunity costs, and strategic dependency costs that go beyond purely technical issues (Eisenhardt, 1989; Salama et al., 2023). These insights also highlight that infrastructural dependency increases firms’ exposure to price volatility and reduces bargaining power, core components of structural economic dependence, thereby strengthening the microeconomic dimension of the research question.

At the political and institutional level, the interviews highlighted the pragmatic manner in which executives approach the concept of digital sovereignty. Although the term itself does not always appear explicitly, its practical relevance emerges in discussions about data protection, data residency, and infrastructure autonomy. As one participant observed: “The term, formally, does not appear so frequently […] but the concept is central. Every time we discuss lock-in, data residency, data protection, infrastructure autonomy […] we are, in practice, talking about digital sovereignty” (Interviewee D). This position reinforces the analyses of Smith et al. (2022) and Luitse and Denkena (2021), who argue that the inability to control critical digital infrastructure compromises informational security, public policy formulation, and the decision-making autonomy of peripheral countries in the international system. The interviews demonstrate that digital sovereignty emerges as an implicit yet constant institutional concern, revealing how infrastructural centralization becomes intertwined with regulatory vulnerability and governance challenges, key elements of the research question’s geopolitical dimension.

Another relevant point concerns the risk that technological dependence may limit the innovation capacity of organizations. As one interviewee stated: “When an organization becomes comfortable and starts consuming only off-the-shelf technology […] it loses internal technical capacity and stops innovating” (Interviewee F). This finding converges with Crawford (2021) and Khanal et al. (2024), who argue that infrastructure centralization not only concentrates economic and computational power but also shapes innovation trajectories, restricting local technological alternatives and perpetuating global asymmetries. The empirical insight illustrates a form of innovation lock-in: by relying on external infrastructures, firms reduce their absorptive capacity, weaken internal R andD processes, and inadvertently reproduce global technological hierarchies, precisely the structural mechanism this study seeks to understand.

Finally, the interviews highlighted mitigation strategies, such as the use of multi-cloud architectures, the development of proprietary solutions, and the strengthening of internal technical teams to reduce critical dependence. These measures align with the technological decentralization proposals advanced by Lim et al. (2022) and Salama et al. (2023), who identify approaches such as edge computing and federated learning pathways to redistribute computational capacities and enhance the resilience of digital ecosystems. These strategies reveal that firms in the Global South are not passive recipients of external technological regimes; rather, they mobilize adaptive capabilities to negotiate infrastructural constraints, offering practical evidence for the pathways through which autonomy can be incrementally rebuilt.

In summary, the empirical findings corroborate the literature by demonstrating that AI infrastructure centralization is not merely a technical phenomenon but also an economic, political, and institutional one, affecting the strategic autonomy of organizations and emerging economies. At the same time, they suggest that building more autonomous and resilient ecosystems requires not only technological investments but also new institutional and regulatory arrangements capable of addressing the asymmetries inherent in the current “Big AI” regime (Ferrari et al., 2023; van der Vlist et al., 2025). Thus, the results directly respond to the research question by revealing that infrastructural dependence reconfigures power relations at multiple levels organizational, national, and geopolitical, demonstrating the multidimensional nature of technological autonomy in the Global South.

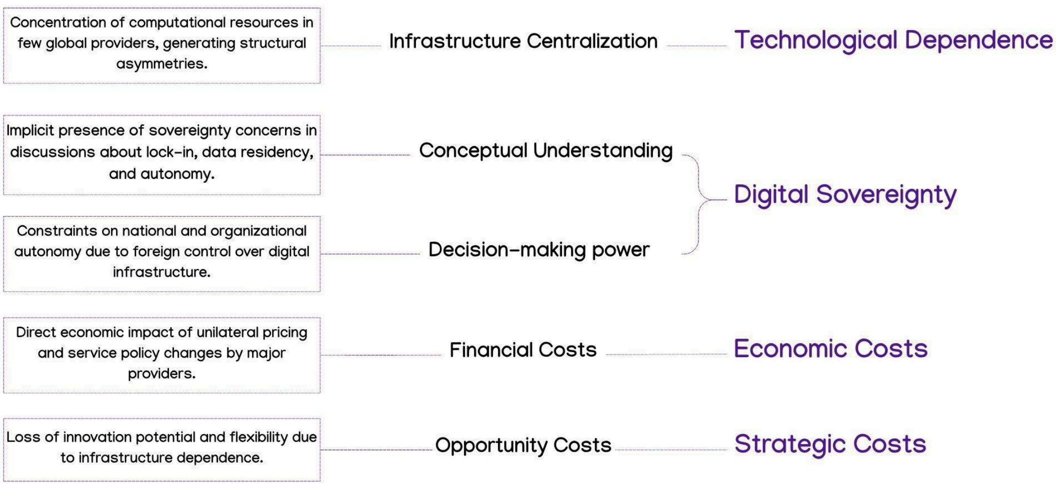

Figure 1 – Coding Tree of the Interview Data (Author, 2025)

The coding process resulted in categories that reflect the main dimensions identified in the interviews. These include Infrastructure Centralization, associated with the concentration of computational resources in a few global providers; Conceptual Understanding, which captures how sovereignty concerns are embedded in discussions about data and autonomy; Decision-Making Power, related to the constraints imposed by foreign control over digital infrastructures; Financial Costs and Opportunity Costs, representing the economic and strategic implications of dependence; all of which converge into three overarching analytical dimensions: Technological Dependence, Digital Sovereignty, and Economic and Strategic Costs.

Taken together, these dimensions synthesize the mechanisms through which infrastructural centralization reshapes firms' autonomy, providing a coherent analytical framework that links the empirical results to the structural, economic, and geopolitical axes of the study.

2.4 Discussion of Results

[In this section, the author undertakes the activity of analyzing the data obtained, relating them to each other in search of answers to the questions raised in the research project, confirming or refuting the hypotheses, approaching or distancing themselves from the presented theoretical framework, comparing them with other results from similar studies, and exploring possible new paths that could advance knowledge about the researched object. In the discussion of the results, the author may provide explanations for the cause-and-effect relationships of the observed phenomena, supporting them with the collected data. Eventually, based on the analysis of the results, it is necessary to elaborate definitions for terms with which the author is working, thus allowing for a better understanding of the work by the reader.]

The analysis of the six semi-structured interviews revealed a consistent pattern in how organizations experience dependence on centralized AI infrastructure. Across all cases, executives described hyperscalers as simultaneously indispensable and strategically risky, emphasizing that the structural concentration of computational resources, data processing capabilities, and proprietary architectures creates a persistent form of infrastructural dependency. Based on these findings, a conceptual framework was developed to represent how this dependency unfolds.

The interviews indicate that centralized AI infrastructure generates dependence through three interconnected mechanisms. The first mechanism concerns governance: participants reported that provider-defined standards, compliance requirements, service architectures, and opaque platform rules constrain internal decision-making and reduce the organization's capacity to manage its own data and systems autonomously. The second mechanism relates to security and data exposure. Firms expressed concerns about cross-border data flows, unilateral changes to security practices, limited visibility into incident response, and the exposure of sensitive information to foreign jurisdictions, all of which diminish their practical control over digital assets. The third mechanism involves economic lock-in, manifested through high switching costs, proprietary services that lack substitutable alternatives, long-term contractual commitments, and unilateral pricing adjustments that weaken bargaining power and limit strategic flexibility.

These mechanisms produce three types of outcomes observed across the organizations studied. The first outcome is technological dependence: reliance on external infrastructure progressively erodes internal capabilities, reduces the ability to build or modify AI systems independently, and constrains experimentation and innovation. The second outcome is a loss of digital sovereignty, as strategic decisions regarding data governance, storage, processing pipelines, and AI tooling become effectively externalized to global providers, falling outside national or organizational institutional control. The third outcome consists of economic and strategic costs, including escalating infrastructure expenditures, migration and switching costs, and opportunity costs related to the inability to diversify providers or develop endogenous technological alternatives.

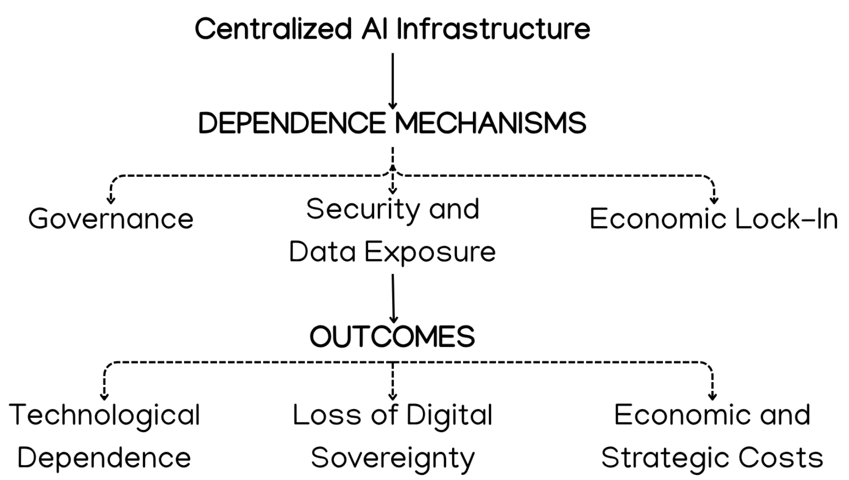

Figure 2 – Framework of Infrastructural Dependence and Technological Autonomy (Author, 2025)

Taken together, these insights show that AI infrastructure centralization operates as a systemic phenomenon that structures organizational autonomy in emerging economies. The resulting framework, summarized in Figure, makes explicit how dependence emerges from governance, security, and economic mechanisms and materializes in technological, sovereign, and strategic constraints. The findings demonstrate that infrastructural centralization reinforces global asymmetries and limits the capacity of organizations and, by extension, states to pursue digital autonomy. This provides a theoretically grounded and empirically supported foundation for the development of governance strategies, regulatory approaches, and organizational responses aimed at reducing long-term structural dependence on centralized AI infrastructure.

3 Conclusion

This study shows that the centralization of AI infrastructure shapes the technological, economic, and institutional autonomy of firms in emerging economies. Through interviews with senior executives, the findings reveal that dependence on hyperscalers is produced by three interconnected mechanisms, governance constraints, security and data-exposure risks, and economic lock-in, which, in turn, generate technological dependence, loss of digital sovereignty, and significant strategic and financial costs.

By organizing these dynamics into an integrated framework, the research advances the understanding of infrastructural dependence as a multidimensional phenomenon rooted in cost asymmetries, geopolitical structures, and uneven control over critical digital resources. Although partial mitigation strategies, such as multi-cloud architectures, internal capability building, and selective decentralization, can reduce exposure in specific areas, none of them fully eliminate the structural vulnerabilities associated with centralized AI ecosystems.

The findings highlight the need for coordinated organizational and policy responses aimed at strengthening local infrastructures, diversifying technological options, and establishing governance mechanisms that balance innovation with autonomy. Future research could expand the empirical base across different regions of the Global South, incorporate comparative analyses with more technologically sovereign countries, and explore quantitative approaches to measuring infrastructural costs and lock-in. Strengthening technological autonomy will require long-term investments, regulatory development, and sustained strategic action to reduce the structural dependencies that currently shape the global AI landscape.

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