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Benchmarking AI Readiness Beyond Economic Complexity: A Qualitative Literature Review of Overperformance Drivers and National Coordination Models

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Abstract: This qualitative literature review examines why some countries demonstrate levels of artificial intelligence (AI) readiness that exceed expectations based on their economic complexity. Building on recent advances in AI preparedness measurement and economic complexity theory, the study synthesizes interdisciplinary literature from economics, innovation studies, AI governance, and development policy. The review finds that economic complexity provides a necessary structural foundation for AI readiness but is insufficient on its own to explain cross-country variation. Countries that overperform relative to their structural constraints consistently benefit from complementary drivers, particularly regulatory and ethical governance frameworks, while digital infrastructure and human capital play context-dependent roles across income levels. The analysis further identifies three dominant national coordination models—state-led, market-responsive, and distributed innovation systems—through which countries translate latent capabilities into applied AI readiness. The study contributes a conceptual benchmark for understanding AI overperformance and offers policy-relevant insights for addressing the global AI divide through context-sensitive institutional design

Keywords: Artificial Intelligence Readiness; Economic Complexity; Institutional Governance; National Innovation Systems; AI Policy Coordination

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1. Introduction

Artificial intelligence (AI) has emerged as a general-purpose technology with profound implications for productivity, economic growth, labor markets, and global competitiveness (Acemoglu, 2024; Aghion et al., 2019; Brynjolfsson & McAfee, 2014). Recent advances in machine learning and generative AI have accelerated diffusion across sectors, intensifying policy debates around national preparedness, governance, and inequality in technological adoption (Brynjolfsson et al., 2025; Korinek, 2024; UNDP, 2025). While high-income economies continue to dominate frontier AI development, an increasing number of middle- and low-income countries demonstrate unexpected progress in AI readiness, challenging deterministic views that link technological capability strictly to income levels or industrial sophistication (Mandon, 2025; Hidalgo, 2023).

Conventional approaches to benchmarking AI readiness rely heavily on composite indices that aggregate indicators of infrastructure, skills, innovation, and governance, such as the IMF's Artificial Intelligence Preparedness Index (AIPI) and Stanford's AI Index (Brynjolfsson & Unger, 2023; HAI, 2025). Although these instruments provide valuable cross-country comparisons, they often fail to account for countries' underlying productive structures and historical development trajectories, which shape the feasible pace and direction of technological adoption (Acemoglu & Robinson, 2012; Hidalgo & Hausmann, 2009). As a result, countries with similar index scores may face fundamentally different constraints and opportunities, obscuring the identification of genuine overperformance in AI preparedness. Technology readiness and organizational learning play a crucial role in the cloud computing adoption strategy among SMEs in Jakarta (Ruslaini, & Muhammad Rizal, 2022).

Economic complexity theory offers a complementary lens by conceptualizing development as a process of accumulating productive knowledge embedded in networks of firms, institutions, and workers (Hidalgo, 2015; Hidalgo & Hausmann, 2009). Multidimensional extensions of the Economic Complexity Index (ECI), incorporating trade, research, and digital product data, enable a richer characterization of national capabilities beyond traditional income measures (Stojkoski et al., 2023; Stojkoski et al., 2024). However, while economic complexity has been widely applied to innovation, green growth, and industrial policy, its integration with AI preparedness metrics remains limited (Hidalgo, 2023). This gap constrains our ability to distinguish structural capability from strategic coordination in national AI trajectories. Digitalization plays a significant role in driving technological innovation in the micro, small, and medium enterprises sector (Chaidir, M., et al, 2024).

This qualitative literature review builds on recent advances by examining AI readiness relative to economic complexity, rather than in absolute terms. Drawing on the framework proposed by Mandon (2025), the study conceptualizes AI preparedness as an outcome that may exceed—or fall short of—what a country's productive structure would predict. Using the IMF's AIPI and a multidimensional ECI derived from trade and research data, the underlying approach estimates expected AI preparedness through weighted least squares and identifies countries whose observed performance significantly surpasses these expectations. Such countries are classified as global overperformers or local overperformers, depending on whether they also exceed the median performance of their income group.

The identification of overperformers is not merely a statistical exercise but raises critical theoretical questions regarding the drivers of AI readiness beyond structural endowments. Existing literature highlights a wide range of potential mechanisms, including regulatory quality, ethical governance, human capital formation, digital infrastructure, and institutional coordination (Acemoglu, 2024; Cazzaniga et al., 2024; UN HLAB-AI, 2024). Importantly, the relevance and effectiveness of these drivers vary across stages of development. For instance, while advanced economies benefit from sophisticated data governance and competition policy, lower-income countries may realize outsized gains from targeted investments in connectivity, public digital platforms, and skills diffusion (Heeks, 2018; Hjort & Poulsen, 2019; World Bank, 2019).

Recent empirical and qualitative studies underscore the central role of regulation and ethics as universal enablers of AI adoption. Clear legal frameworks reduce uncertainty, foster trust, and facilitate coordination among public and private actors, regardless of income level (European Commission, 2024; PRC MIIT, 2024; UNDP, 2025). At the same time, digital infrastructure and human capital exhibit strong context dependence. In emerging economies such as Rwanda, India, or Ghana, strategic public investment and international partnerships have compensated for limited industrial depth, enabling AI experimentation in public services and small-state innovation ecosystems (IMF, 2023; F.O.S.S. Digital, 2024; Mandon, 2025). These findings resonate with broader development literature emphasizing institutional adaptability and policy learning over static resource endowments (Fagerberg et al., 2010; Sala-i-Martin et al., 2004).

Beyond identifying drivers, understanding how countries coordinate AI development is crucial. The literature increasingly points to distinct national coordination models, ranging from state-led strategies to market-responsive systems and distributed innovation networks (Durand, 2024; Korinek & Vipra, 2024). State-led models, exemplified by China or Singapore, rely on centralized planning, standards, and public infrastructure to accelerate diffusion (de Seta, 2023; PRC MIIT, 2024). Market-responsive models, common in Northern Europe, emphasize regulatory clarity, competition, and firm-level experimentation (European Commission, 2024). Distributed innovation models, often observed in smaller or lower-income economies, leverage public–private partnerships, international organizations, and diaspora knowledge flows to overcome scale constraints (Valette, 2018; F.O.S.S. Digital, 2024).

However, the transferability of these coordination models is inherently limited. Historical legacies, political institutions, cultural norms, and administrative capacity shape the feasibility of adopting best practices across contexts (Acemoglu & Robinson, 2012; Todd, 2019; Kung & Ma, 2014). Consequently, benchmarking AI readiness must move beyond rankings toward context-sensitive interpretation, recognizing that overperformance often reflects strategic alignment rather than universal policy recipes.

Against this backdrop, this qualitative literature review makes three main contributions. First, it advances the conceptualization of AI readiness by synthesizing research that integrates AI preparedness indices with economic complexity, enabling a more nuanced assessment of overperformance relative to structural conditions (Hidalgo, 2023; Mandon, 2025). Second, it systematically reviews evidence on coordination mechanisms underlying AI readiness, distinguishing state-led, market-responsive, and distributed innovation models while highlighting their institutional prerequisites and limitations. Third, it critically evaluates existing AI preparedness metrics, particularly their applicability in lower-income contexts, and identifies avenues for refinement, including the incorporation of governance quality, AI literacy, and alternative data sources (Lintner, 2024; Ongena, 2023; Yang et al., 2025). Effective corporate governance and sustainable leadership will help a company perform much better (Kusnanto, E., 2022).

By synthesizing these strands, the study aims to equip policymakers, scholars, and international institutions with a replicable and analytically grounded framework to benchmark AI readiness, identify meaningful overperformance, and design strategies tailored to national capabilities. In doing so, it contributes to ongoing efforts to address the global AI divide and ensure that the benefits of AI-driven transformation are broadly shared across diverse economic and institutional landscapes (UNDP, 2025; UNSD, 2024).

2. Literature Review

AI Readiness, Economic Growth, and Structural Constraints. The growing body of literature conceptualizes artificial intelligence (AI) as a general-purpose technology capable of reshaping productivity, labor markets, and long-term economic growth trajectories across countries (Acemoglu, 2024; Aghion et al., 2019; Brynjolfsson & McAfee, 2014). Macroeconomic models emphasize that AI-driven growth is neither automatic nor uniform, as its impact depends on complementary investments in skills, institutions, and governance frameworks (Acemoglu & Restrepo, 2018; Trammell & Korinek, 2023). Empirical evidence further suggests that AI adoption amplifies existing structural advantages unless counterbalanced by inclusive policies and coordination mechanisms (Autor, 2015; Korinek, 2024).

Traditional explanations of cross-country technological divergence draw heavily on institutional quality and historical political economy, arguing that extractive institutions constrain innovation regardless of technological opportunity (Acemoglu & Robinson, 2012). However, recent AI-specific studies demonstrate that countries with weaker industrial bases may still achieve meaningful AI adoption when coordination failures are addressed through regulation, public investment, and targeted capability building (Brynjolfsson & Unger, 2023; UNDP, 2025). These findings challenge linear development models and motivate the need for benchmarking frameworks that adjust for structural constraints.

Economic Complexity and the Measurement of Productive Capabilities. Economic complexity theory provides a structural lens for understanding why countries differ in their ability to adopt and diffuse advanced technologies, including AI (Hidalgo & Hausmann, 2009; Hidalgo, 2015). The Economic Complexity Index (ECI) operationalizes this perspective by measuring the diversity and sophistication of a country's productive knowledge embedded in trade and innovation networks (Hidalgo & Hausmann, 2009). Empirical research shows that higher economic complexity is strongly associated with innovation capacity, institutional quality, and long-run growth (Fagerberg et al., 2010; Sala-i-Martin et al., 2004).

Recent advances extend economic complexity into multidimensional frameworks incorporating research outputs, digital trade, and intangible assets, enabling more granular assessments of national capabilities in the digital economy (Stojkoski et al., 2023; Stojkoski et al., 2024). Hidalgo (2023) argues that such multidimensional complexity measures are particularly relevant for AI, as digital technologies rely on non-rival, combinatorial knowledge rather than physical capital alone. Nonetheless, complexity-based approaches alone cannot explain why some countries outperform expectations in AI readiness, highlighting the importance of strategic coordination beyond structural endowments (Hidalgo, 2023).

AI Preparedness Indices and Their Limitations. AI preparedness indices, such as the IMF's Artificial Intelligence Preparedness Index (AIPI) and Stanford's AI Index, have become central tools for cross-country comparison and policy benchmarking (Brynjolfsson & Unger, 2023; HAI, 2025). These indices typically aggregate indicators related to digital infrastructure, human capital, innovation ecosystems, regulation, and ethics (Cazzaniga et al., 2024; UN HLAB-AI, 2024). Empirical applications show strong correlations between AI preparedness scores and income levels, reinforcing concerns that such indices may conflate readiness with development status (UNDP, 2025).

Critiques emphasize that composite indices often overlook context-specific constraints, informal innovation systems, and alternative pathways to AI adoption in lower-income economies (Heeks, 2018; Cariolle & Aker, 2023). Moreover, measurement bias may underestimate preparedness in countries where AI deployment occurs through public-sector experimentation or frugal innovation rather than frontier research (IMF, 2023; Mortier et al., 2025). These limitations motivate analytical approaches that benchmark AI preparedness relative to underlying productive structures rather than absolute scores.

AI Overperformance Relative to Economic Complexity. Mandon (2025) provides a pivotal contribution by integrating AI preparedness metrics with economic complexity to identify countries that outperform expectations given their structural conditions. Using weighted least squares estimation, the study demonstrates that a subset of countries consistently exceeds predicted AI preparedness levels, even after controlling for income group medians (Mandon, 2025). Empirical results identify high-income global overperformers such as Northern European countries and Singapore, alongside local overperformers across middle- and low-income groups, including China, India, Malaysia, Rwanda, and Ghana (Mandon, 2025).

The findings reveal that overperformance is not driven solely by technological sophistication but by coordinated investments in regulation, ethics, and institutional alignment (Mandon, 2025). These results align with earlier innovation studies showing that policy coherence and institutional adaptability can compensate for limited industrial depth (Fagerberg et al., 2010; Rogers, 2003). Importantly, Mandon's framework demonstrates methodological replicability, offering a robust benchmark for comparative AI readiness analysis across heterogeneous contexts (Mandon, 2025).

Drivers of AI Readiness: Regulation, Infrastructure, and Human Capital. Across the literature, regulation and ethical governance emerge as universal drivers of AI readiness, reducing uncertainty and enabling trust among firms, governments, and users (UN HLAB-AI, 2024; European Commission, 2024). Comparative studies show that clear standards and data governance frameworks facilitate AI diffusion regardless of income level, particularly in small states and emerging economies (F.O.S.S. Digital, 2024; PRC MIIT, 2024). Empirical evidence further indicates that regulatory clarity complements market experimentation rather than constraining innovation (Korinek & Vipra, 2024).

Digital infrastructure and human capital exhibit stronger context dependence, with their marginal impact varying by development stage (Hjort & Poulsen, 2019; World Bank, 2019). Studies on Africa and Southeast Asia demonstrate that connectivity investments yield significant employment and productivity gains when paired with institutional reforms and skills development (Cariolle & Aker, 2023; IMF, 2023). Human capital quality, including AI literacy and data skills, increasingly shapes effective AI adoption, as confirmed by systematic reviews of AI education and literacy frameworks (Lintner, 2024; Yang et al., 2025).

National Coordination Models for AI Development. The literature identifies three dominant national coordination models underpinning AI readiness: state-led, market-responsive, and distributed innovation systems (Durand, 2024; Korinek, 2024). State-led models, exemplified by China and Singapore, rely on centralized planning, standards, and public digital infrastructure to accelerate AI diffusion across sectors (de Seta, 2023; PRC MIIT, 2024). Empirical studies show that such models can rapidly scale AI capabilities but require strong administrative capacity and political legitimacy (Durand, 2024).

Market-responsive models, common in Northern Europe, emphasize regulatory predictability, competition policy, and firm-level experimentation (European Commission, 2024). Evidence suggests that these systems foster incremental innovation and ethical AI deployment, particularly in high-trust institutional environments (Vaccaro et al., 2024). Distributed innovation models, observed in smaller or lower-income economies, leverage public–private partnerships, international organizations, and diaspora networks to overcome scale and resource constraints (F.O.S.S. Digital, 2024; Valette, 2018).

Transferability Constraints and Contextual Embeddedness. Despite growing interest in best-practice diffusion, the literature consistently cautions against the uncritical transfer of AI coordination models across contexts (Acemoglu & Robinson, 2012; Todd, 2019). Institutional histories, cultural norms, and administrative capabilities shape how AI strategies are implemented and sustained (Kung & Ma, 2014; Ongena, 2023). Empirical evidence from development economics shows that policy imitation without institutional fit often yields limited or adverse outcomes (Heeks, 2018; World Bank, 2024).

Consequently, overperformance in AI readiness should be interpreted as context-specific alignment rather than universal superiority (Mandon, 2025). This insight reinforces calls for benchmarking frameworks that integrate structural conditions, governance quality, and coordination mechanisms into comparative analysis (Hidalgo, 2023; UNDP, 2025).

Synthesizing the literature, AI readiness emerges as a multidimensional outcome shaped by productive capabilities, institutional quality, and national coordination models rather than income or technological sophistication alone (Acemoglu, 2024; Mandon, 2025). While economic complexity provides a powerful baseline for structural capacity, overperformance arises from strategic governance, regulatory coherence, and adaptive coordination (Hidalgo, 2023). Existing studies, however, remain fragmented across disciplines and often lack integrative frameworks that connect structural benchmarking with qualitative institutional analysis.

This qualitative literature review addresses this gap by systematically synthesizing research on AI preparedness, economic complexity, and coordination models to explain why certain countries outperform expectations. By doing so, it contributes to a more nuanced understanding of AI readiness and provides a conceptual foundation for policy-relevant benchmarking beyond economic complexity alone.

3. Proposed Method

In this section, you need to describe the proposed method step by step. Explanations accompanied by equations and flow diagrams as illustrations will make it easier for readers to understand your research.

This study adopts a qualitative literature review design to systematically synthesize empirical and theoretical contributions on AI readiness benchmarking relative to economic complexity, overperformance drivers, and national coordination models. Qualitative literature review is an interpretive research approach that enables in-depth integration of conceptual frameworks and empirical evidence across diverse sources (Bryman, 2016; Webster & Watson, 2002). This method is particularly suited for synthesizing complex, multidisciplinary fields such as AI policy, economic complexity, and innovation governance where experimental or purely quantitative aggregation is insufficient to capture contextual nuance (Cooper, 2016; Torraco, 2005).

Qualitative review offers a replicable but flexible analytical structure that goes beyond mere aggregation, facilitating the construction of higher-order themes and causal mechanisms across studies (Denzin & Lincoln, 2018). In this study, the methodology is guided by frameworks for systematic narrative synthesis, which emphasize transparency, rigor, and reflexivity in integrating literature (Popay et al., 2006; Petticrew & Roberts, 2006).

The literature corpus was assembled from multiple interdisciplinary databases to ensure coverage of both technical AI research and policy–innovation literature. Search terms were developed iteratively using combinations of keywords related to the study objectives, such as: “AI readiness”, “Artificial intelligence preparedness”, “Economic complexity”, “Innovation systems”, “Overperformance”, “National coordination model,” and “Policy frameworks.” These terms were selected based on emerging themes in leading AI indices and innovation governance scholarship (Brynjolfsson et al., 2025; HAI, 2025). Boolean search operators and controlled vocabulary were used to enhance precision and recall (Boell & Cecez-Kecmanovic, 2014). The initial search yielded an extensive set of peer-reviewed journal articles, authoritative reports, working papers, and policy documents. Each retrieved document’s relevance was screened based on title and abstract against inclusion criteria described below.

This study applies explicit inclusion and exclusion criteria to ensure methodological consistency and empirical relevance. Sources were included if they: Focus on AI readiness, preparedness indices, or benchmarking frameworks (e.g., AI indices by IMF or Stanford AI Index) (Brynjolfsson & Unger, 2023; HAI, 2025). Address economic complexity or productive capabilities in relation to technological adoption (Hidalgo, 2023; Hidalgo & Hausmann, 2009). Discuss drivers of technological overperformance, including regulation, infrastructure, or human capital (Mandon, 2025; Korinek, 2024). Present evidence, frameworks, or case studies on national coordination models of AI and innovation governance (European Commission, 2024; PRC MIIT, 2024).

Sources were excluded if they focused solely on narrow technical aspects of AI systems without relevance to policy, innovation, or economic benchmarking (e.g., algorithm optimization papers), or if they predated decentralization of AI policy discourse before 2015, which serves as a reasonable cutoff given the rapid evolution of AI governance scholarship (Brynjolfsson & McAfee, 2014; Bostrom, 2014).

Following screening, relevant full texts were imported into a reference management tool (e.g., EndNote, Zotero) to organize citations and remove duplicates. A structured data extraction form was developed to capture the following components from each source: Bibliographic details (author, year, journal / publisher), Study context and objectives, Conceptual definitions (e.g., AI readiness, economic complexity), Methodological approach, Key findings related to overperformance drivers and coordination models, Implications for benchmarking frameworks. This structured extraction aligns with best practices in qualitative synthesis and helps ensure analytical consistency across heterogeneous sources (Hannes & Lockwood, 2011; Kiger & Varpio, 2020).

Data analysis was conducted using a thematic synthesis approach, which is widely applied in qualitative literature review to identify recurring patterns, conceptual linkages, and explanatory mechanisms across studies (Thomas & Harden, 2008; Lucas et al., 2007). A priori themes were developed based on the research objectives—namely, benchmarking frameworks, drivers of AI readiness, and coordination models—but were refined iteratively through open coding (Charmaz, 2014; Saldaña, 2021).

Coding was conducted in stages: Open Coding: Initial attachment of descriptive codes to extracted data segments. Axial Coding: Grouping of codes into thematic clusters such as regulation & ethics, digital infrastructure, human capital, institutional frameworks, and governance models (Corbin & Strauss, 2015). Selective Coding: Integration of thematic clusters into evidence-based narrative threads that explain why and how certain countries outperform relative to economic complexity (Mandon, 2025; Hidalgo, 2023). This layered approach promotes both analytical depth and conceptual clarity, facilitating connections among structural conditions, policy interventions, and national outcomes.

To enhance the trustworthiness and credibility of synthesized findings, the study incorporates quality appraisal criteria that assess source validity, methodological transparency, and evidentiary strength. Sources were evaluated using adapted frameworks from systematic review guidelines (Booth et al., 2016; Dixon-Woods et al., 2006), focusing on research design, data quality, theoretical coherence, and relevance to AI readiness discourse.

Reflexivity was maintained by explicitly acknowledging the researcher's subjective positioning, particularly in interpreting policy and qualitative evidence (Berger, 2015; Finlay, 2002). Through iterative memoing and triangulation of diverse source types, the analysis mitigates the risk of undue bias or selective interpretation.

Findings are presented through a narrative synthesis that juxtaposes theoretical constructs with empirical evidence. The framework synthesizes research on: Benchmarking approaches (e.g., integration of AI indices with economic complexity). Drivers of overperformance across income groups. Coordination models of national AI ecosystems (Popay et al., 2006). This multi-modal reporting enhances interpretability and supports policy-relevant insights for scholars and decision-makers alike.

4. Results

In this section, the author needs to explain the hardware and software used, dataset sources, initial data analysis, results, and results analysis/discussion. Presenting the results with pictures, graphs and tables is highly recommended. Formulas or evaluation measuring tools also need to be included here. There must be discussion/analysis, and you can't just rewrite the results in sentence form, but you need to provide an explanation of their relationship to the initial hypothesis. In addition, this section needs to discuss and elaborate on important findings.

The Landscape of AI Preparedness and Economic Complexity. Across the literature, AI readiness is acknowledged as a multidimensional construct incorporating technological infrastructure, human capital, regulatory frameworks, and innovation capabilities (Brynjolfsson & Unger, 2023; HAI, 2025). Traditional indices such as the IMF's Artificial Intelligence Preparedness Index (AIPI) and the Stanford AI Index capture these dimensions but often correlate strongly with income and conventional development indicators (Brynjolfsson & Unger, 2023; HAI, 2025). This pattern aligns with classic development research showing that higher income, diversified productive structures, and complex capabilities generally support innovation adoption (Hidalgo & Hausmann, 2009; Fagerberg et al., 2010). However, such indices alone cannot explain why some countries perform better than expected relative to their structural profiles, motivating the need to benchmark AI readiness beyond economic complexity.

Economic complexity theory posits that the diversity and sophistication of a country's productive knowledge determine its capacity to adopt and benefit from advanced technologies (Hidalgo & Hausmann, 2009; Hidalgo, 2023). Complexity measures have demonstrated predictive power for economic growth and innovation, even after controlling for income (Hidalgo, 2023; Stojkoski et al., 2023). Yet, complexity does not fully account for overperformance—instances where countries achieve higher levels of AI readiness than would be predicted by their economic complexity and income profiles. Identifying and explaining these deviations constitutes a central empirical finding of recent research.

Identification of Overperformers Relative to Economic Complexity. Mandon's (2025) framework is the primary empirical contribution underpinning this review. By integrating the AIPI with a multidimensional Economic Complexity Index (ECI) derived from trade and research data, Mandon (2025) estimates expected AI preparedness scores through weighted least squares and identifies countries that outperform structurally predicted levels. This operationalization yields two categories: global overperformers—countries exceeding predicted AI readiness and outperforming within the high-income group—and local overperformers—countries exceeding predicted readiness relative to their own income group's median.

Empirical results from Mandon (2025) identify 10 global overperformers primarily in Northern Europe and East Asia, including Nordic countries and Singapore, as well as 14 local overperformers spanning middle- and low-income groups, such as China, India, Malaysia, Rwanda, and Ghana. These findings demonstrate that economic complexity is necessary but not sufficient to explain AI readiness outcomes.

Drivers of Overperformance: Regulation, Infrastructure, and Human Capital. A central theme emerging from the literature is that institutional and governance factors, especially regulation and ethical frameworks, consistently differentiate overperformers from non-overperformers across income levels. Regulatory clarity, data governance standards, and ethical AI guidelines reduce uncertainty for both public and private actors, enabling broader adoption and experimentation (European Commission, 2024; UN HLAB-AI, 2024). These institutional drivers align with broader macroeconomic analyses showing that policy frameworks shape technological diffusion beyond structural endowments (Korinek, 2024; Korinek & Vipra, 2024).

Digital infrastructure—including broadband access, digital platforms, and data ecosystem maturity—emerges as another key driver of AI readiness, particularly for middle-income overperformers. Studies show that investments in connectivity significantly increase adoption opportunities, employment, and productivity when coupled with complementary policies (Hjort & Poulsen, 2019; World Bank, 2019). For example, Rwanda's strategic focus on broadband and public-sector e-services, supported by partnerships such as the F.O.S.S. Digital playbook for small states, appears to underpin its overperformance relative to structural predictors (F.O.S.S. Digital, 2024; IMF, 2023).

Human capital quality and AI literacy also differentiate overperformers. While complexity captures broad research capacity, it does not capture workforce skills directly. Systematic reviews highlight that AI literacy, data literacy, and human-AI collaboration competencies are increasingly critical for readiness (Lintner, 2024; Vaccaro et al., 2024; Yang et al., 2025). Nations that have invested in education, retraining, and inclusive digital skills development exhibit higher AI readiness than expected, even with moderate structural complexity.

Coordination Models Underpinning Overperformance. The literature indicates that distinct national coordination models facilitate overperformance in AI readiness. Three clusters emerge:

a. State-Led Models: Countries like China and Singapore combine strategic planning, comprehensive standards, and significant public investment in digital infrastructure to accelerate AI adoption (de Seta, 2023; PRC MIIT, 2024). China's national AI industrial standards initiative exemplifies how centralized coordination can align research, industry, and regulation, generating overperformance relative to structural constraints.

b. Market-Responsive Models: Northern European countries, while structurally complex, pair their sophistication with regulatory transparency and market dynamics that support firm-level innovation and ethical application of AI (European Commission, 2024). This model emphasizes regulatory predictability, competition policy, and ecosystems that allow diversified innovation paths.

c. Distributed Innovation Models: Smaller or lower-income economies often rely on distributed networks of public institutions, private actors, international partners, and diaspora knowledge flows to enable AI adoption. Research indicates that these models are effective for leveraging comparative advantages despite limited structural depth (F.O.S.S. Digital, 2024; Valette, 2018). Case evidence from Rwanda and Ghana, for example, reflects the use of targeted partnerships and adaptive governance to achieve readiness beyond structural expectations (IMF, 2023; Mandon, 2025).

Across models, success hinges on coordination capacity—the ability to align actors, set priorities, and bridge gaps between research, policy, and market adoption. This insight aligns with broader innovation systems research, which emphasizes institutional complementarities and the role of governance in shaping outcomes (Fagerberg et al., 2010; Heeks, 2018).

Transferability and Contextual Limits. Despite identifying common drivers and coordination archetypes, the literature also highlights contextual constraints on transferability. Institutional histories, political systems, cultural norms, and administrative capacity condition how strategies are implemented and whether they yield comparable results (Acemoglu & Robinson, 2012; Kung & Ma, 2014). For instance, regulations that promote competition and ethical AI in high-trust societies may produce different outcomes in contexts with weaker enforcement capacity. Similarly, digital infrastructure investments may yield limited returns without supportive educational systems and complementary policies (Heeks, 2018; World Bank, 2024).

These findings suggest that benchmarking frameworks should not only measure readiness levels but also interpret results in light of institutional and historical contexts. This approach reduces the risk of misinterpreting overperformance as purely replicable success rather than as contextually contingent alignment of capabilities and strategies.

The qualitative synthesis reveals several gaps and research opportunities. Metrics Refinement: Existing indices (AIPI, AI Index) inadequately capture governance quality, AI literacy, and informal innovation ecosystems, particularly in lower-income settings. Future work should integrate these dimensions into composite metrics (Lintner, 2024; Yang et al., 2025). Comparative Innovation Systems: More comparative studies are needed to systematically analyze how coordination models operate within different political and economic contexts, including longitudinal case evidence.

Microfoundations of Overperformance: Research focused on firm-level and sector-level adoption patterns could enrich understanding of how national readiness translates into economic and social outcomes (Babina et al., 2024; Noy & Zhang, 2023). Policy Experimentation: Evaluations of targeted policy interventions (e.g., data governance reforms, AI skills programs) in lower-income countries would clarify causal mechanisms behind overperformance.

The literature indicates that: Economic complexity is a strong baseline predictor of AI readiness but does not fully account for observed outcomes across countries (Hidalgo & Hausmann, 2009; Hidalgo, 2023). Overperformance relative to complexity emerges in contexts with strong regulation, digital infrastructure, and human capital investments (Mandon, 2025; European Commission, 2024; Lintner, 2024). Coordination models—state-led, market-responsive, and distributed innovation—provide distinct pathways for achieving readiness beyond structural constraints (de Seta, 2023; F.O.S.S. Digital, 2024). Contextual factors condition the transferability and effectiveness of strategies, underscoring the need for context-sensitive benchmarking frameworks (Acemoglu & Robinson, 2012; Heeks, 2018). Collectively, these findings provide a nuanced, evidence-based understanding of why and how certain countries outperform their structural expectations in AI readiness, offering a foundation for both scholarly inquiry and policy design.

5. Discussion

The primary objective of this qualitative literature review was to synthesize empirical and theoretical insights on why certain countries demonstrate AI readiness that outperforms expectations based on economic complexity, and to identify the drivers and coordination models that underpin such overperformance. The review finds that while economic complexity provides a foundational capacity for innovation and technological adoption, institutional quality, regulatory frameworks, infrastructure investments, human capital, and national coordination models serve as critical enabling conditions for elevated AI readiness. These findings align in part with existing studies but also highlight important nuances and contextual differences that emerge when benchmarking readiness relative to structural constraints.

Economic Complexity as a Baseline. Consistent with the economic complexity literature, multidimensional complexity indices—incorporating research, industrial breadth, and digital trade—correlate positively with innovation capacity and AI readiness (Hidalgo & Hausmann, 2009; Hidalgo, 2023). However, complexity alone explains only part of the variation in national AI preparedness. This supports earlier findings in the innovation economics literature showing that structural capabilities are necessary but not sufficient for technological leadership and adoption (Fagerberg, Srholec, & Verspagen, 2010; Sala-i-Martin, Doppelhofer, & Miller, 2004). While prior research demonstrated strong links between complexity and broad economic outcomes, this review highlights that AI readiness specifically requires additional governance and coordination mechanisms that structure how complexity translates into action (Hidalgo, 2023; Mandon, 2025).

Regulation and Institutional Coordination. One of the most robust themes across the literature is the central role of regulation and institutional governance in supporting AI readiness beyond what structural capacity would predict. Studies from the European Commission (2024) emphasize that regulatory certainty, ethical AI guidelines, and data protection frameworks enhance trust and lower adoption barriers, enabling businesses and public institutions to leverage AI more effectively. Similarly, UN HLAB-AI (2024) argues that global governance standards help harmonize expectations, reduce policy fragmentation, and foster cross-border cooperation.

These findings converge with Korinek's (2024) macroeconomic analysis, which posits that effective policy frameworks reduce uncertainty and enhance returns on investment in emerging technologies. In contrast, contexts with weak regulation may face stasis despite structural potential, as firms and governments lack guidance on liability, privacy, and competitive norms. This contrasts with Chui et al.'s (2023) McKinsey report, which highlights that many countries with significant digital infrastructure still lag in AI adoption due to regulatory and institutional gaps. Collectively, these studies emphasize that regulatory quality and clarity are foundational enablers that mediate the translation of complexity into readiness.

Digital Infrastructure and Public Investment. Digital infrastructure emerges as another key overperformance driver, especially in middle-income contexts. The literature reviewed suggests that connectivity, reliable broadband, and digital public goods reduce friction in both private and public AI applications (Hjort & Poulsen, 2019; World Bank, 2019). Rwanda's explicit focus on broadband expansion and e-services, supported through public–private partnerships such as the F.O.S.S. Digital initiative, illustrates how targeted infrastructure investments can elevate readiness beyond structural expectations (F.O.S.S. Digital, 2024; IMF, 2023). This echoes findings by Brynjolfsson & Unger (2023), who highlight the role of broad digital access in enabling small firms and governments to experiment with AI tools.

By comparison, Choudhary, Ruch, and Skrok (2024) find that infrastructure alone does not guarantee adoption unless accompanied by complementary institutional reforms. Their analysis of taxation and economic policy suggests that without a supportive business climate and efficient public administration, infrastructural investments may not translate into productive AI deployment. Therefore, infrastructure should be seen as necessary but not self-sufficient, reinforcing the broader pattern that drivers of overperformance are multidimensional and interdependent.

Human Capital and AI Literacy. Human capital quality is widely acknowledged as critical for AI readiness (Lintner, 2024; Yang et al., 2025). Countries with robust education systems, strong technical training programs, and continuous reskilling initiatives display readiness that exceeds complexity-based expectations. Systematic reviews of AI literacy highlight that digital skills and competencies are essential for effective implementation and governance of AI technologies (Yang et al., 2025). This is consistent with Vaccaro, Almaatouq, and Malone (2024), who show in their meta-analysis that human–AI team performance strongly correlates with education and interdisciplinary competencies.

However, the relationship between human capital and overperformance varies by context. For example, provisioning high-end AI research talent appears more crucial in high-income economies, whereas in lower-income countries, broad digital literacy and application skills (rather than frontier research skills) are more central to elevating readiness relative to structural constraints. This nuance suggests that policy interventions must be targeted and context-specific, tailoring human capital strategies to the level of economic development and existing institutional capabilities.

National Coordination Models. A key contribution of this review is the identification and comparison of three dominant coordination models that enable overperformance: state-led, market-responsive, and distributed innovation systems. These archetypes reflect distinct ways in which public and private actors align strategies, resources, and regulatory frameworks to enhance AI readiness.

State-Led Models: Countries such as China and Singapore illustrate how centralized strategy, comprehensive national standards, and public investment can catalyze AI adoption. The PRC Ministry of Industry and Information Technology's (MIIT) comprehensive AI standards initiative provides a structured platform to align industry, research, and policy, producing outcomes that exceed what complexity metrics alone would predict (PRC MIIT, 2024; de Seta, 2023). This model's effectiveness aligns with Durand's (2024) argument that purposeful coordination of digital governance can accelerate technological adoption. However, the state-led model may face challenges related to flexibility and local innovation dynamics, especially in heterogeneous market environments.

Market-Responsive Models: Northern European economies exemplify market-responsive coordination, emphasizing regulatory clarity, competition policy, and ecosystem support rather than centralized planning. The European Commission's strategy emphasizes enabling frameworks that allow firms to innovate while maintaining ethical standards and social protections (European Commission, 2024). This model resonates with innovation systems research showing that institutional ecosystems and market incentives are pivotal to sustained technological progress (Fagerberg et al., 2010). The market-responsive approach may be particularly effective in high-trust environments with strong institutional enforcement.

Distributed Innovation Models: In smaller and lower-income economies, AI readiness often emerges through distributed networks involving government, international partners, NGOs, diaspora communities, and private sector innovators. The F.O.S.S. Digital playbook and its implementation through collaborative platforms in Rwanda and other small states illustrate this model's capacity to pool resources and expertise, fostering readiness that outstrips structural predictions (F.O.S.S. Digital, 2024). Valette's (2018) study on knowledge transfer via migrant networks highlights how distributed models leverage mobility and transnational linkages to offset local resource constraints.

These coordination models are not mutually exclusive; many countries blend elements of each based on institutional histories, political systems, and development priorities. The literature indicates that fit to context, rather than adherence to a particular model, often determines overperformance. For instance, while Singapore's state-led model works well given its governance capacity and scale, similar approaches might be less effective in contexts with limited public administration capacity.

Comparing the findings of this review with eight prior studies highlights both convergence and divergence in understanding AI readiness. Mandon (2025): Establishes the foundational integrated framework combining AIPI and ECI, demonstrating measurable overperformance in specific country cases. This study provides the quantitative anchor that complements the qualitative synthesis in this review. Hidalgo & Hausmann (2009) / Hidalgo (2023): Provide the complexity foundations that contextualize structural capacity. This review extends their insights by emphasizing institutional drivers that mediate complexity's translation into AI readiness. European Commission (2024): Offers evidence that market-responsive coordination and regulatory clarity are key enablers, aligning with the findings on the importance of governance frameworks.

Brynjolfsson & Unger (2023): Highlight macroeconomic impacts of AI infrastructure, reinforcing the theme that connectivity and data ecosystems are central to readiness. Lintner (2024) / Yang et al. (2025): Emphasize human capital and AI literacy, validating this review's conclusion that education and skills are critical and vary by development context. F.O.S.S. Digital (2024): Illustrates distributed innovation models in small states, showing how collaborative frameworks can overcome structural limitations. Korinek (2024) & Korinek & Vipra (2024): Provide macroeconomic perspectives on policy frameworks and market structures, underscoring the necessity of regulatory and competition policy in shaping outcomes. Hjort & Poulsen (2019): Demonstrate that digital connectivity significantly influences employment and adoption patterns, supporting the infrastructural driver of overperformance identified in this review. Together, these studies converge on the idea that structural capacity, while necessary, is insufficient without complementary governance, coordination, and human capital strategies. However, they diverge in emphasis: some prioritize macro policy frameworks, others focus on human capital or firm-level innovation ecosystems. This review unifies these strands by situating them within a benchmarking framework that explicitly accounts for structure, drivers, and coordination models.

The synthesis has clear implications for policymakers. AI readiness policies should integrate regulatory clarity, ethical frameworks, and infrastructure investments tailored to contextual strengths and limitations. Human capital interventions must align with national structural capacities, focusing on digital literacy and adaptable competencies in lower-income settings. Coordination models should be chosen with attention to institutional capacity, blending state, market, and distributed elements where appropriate.

For researchers, the review highlights gaps: The need for refined metrics that capture governance quality and AI literacy. Comparative studies on how coordination models operate across diverse political and cultural contexts. Benchmarking AI readiness relative to economic complexity reveals that overperformance arises from multifaceted drivers and strategic coordination, not structural capacity alone. Institutional governance, regulatory quality, digital infrastructure, human capital, and tailored coordination models collectively shape national AI readiness outcomes, offering a nuanced understanding that advances beyond complexity metrics. Future research should continue expanding empirical evidence and refining measurement paradigms to support more equitable global AI development.

6. Conclusions

This qualitative literature review set out to examine why certain countries demonstrate levels of artificial intelligence (AI) readiness that exceed expectations derived from their economic complexity and to identify the institutional drivers and national coordination models underlying such overperformance. Synthesizing insights from economics of innovation, AI governance, development studies, and comparative political economy, the review confirms that economic complexity constitutes a necessary but insufficient foundation for AI readiness. Countries that outperform their structural endowments do so through complementary institutional, regulatory, infrastructural, and human-capital mechanisms that enable the effective translation of latent capabilities into applied AI capacity.

The review highlights regulation and ethical governance as universal drivers of AI overperformance across income groups, underscoring the importance of legal clarity, data protection, and trust-building frameworks in reducing uncertainty and accelerating adoption. In contrast, digital infrastructure and human capital operate as context-dependent drivers, playing differentiated roles depending on levels of economic development, institutional maturity, and state capacity. These findings extend existing economic complexity and AI readiness frameworks by demonstrating that institutional quality and policy coordination mediate the relationship between structural capacity and technological preparedness.

A central contribution of this review is the identification of three dominant national coordination models—state-led, market-responsive, and distributed innovation systems—that shape AI readiness trajectories. Rather than prescribing a single optimal pathway, the findings emphasize institutional fit and adaptability, showing that successful AI strategies are those aligned with historical, political, and administrative contexts. This insight reinforces the importance of policy design that is not only evidence-based but also context-sensitive.

Overall, the review contributes to the literature by integrating AI preparedness indices with economic complexity theory, offering a structured explanation for cross-country heterogeneity in AI readiness. For policymakers, the findings provide actionable guidance for designing AI strategies that go beyond infrastructure investment alone, emphasizing governance, coordination, and human capability development as critical levers for narrowing the global AI divide

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