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# Data-Driven Disintermediation in Green Technology Supply-Demand Matching: Mechanisms and Evidence

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Abstract: Despite the surge in green innovation, technology transfer remains constrained by high search frictions and trust deficits that traditional human-centric intermediation struggles to resolve. Grounded in Transaction Cost Theory, this study conducts an exploratory dual-case study of the "Zhizhe" Model and "Anxinwu" Platform in China to investigate how data elements reconstruct this mechanism. The findings reveal a "Dual-Drive Mechanism" where AI-enabled semantic alignment reduces ex-ante search costs, while blockchain-based evidence chains mitigate ex-post trust costs by substituting bureaucratic endorsement. We conclude that digitization leads to "Functional Disintermediation" — decoupling routine matching and verification from human agents — contingent upon "Techno-Institutional Co-evolution".

**Keywords:** Green Technology Transfer; Data Elements; Functional Disintermediation

## 1.Introduction

Addressing climate change has become a global imperative, driving a surge in green innovation under the impetus of the UN Sustainable Development Goals (Gan, 2025). Governments and research institutions worldwide have invested heavily in R&D, resulting in an exponential growth of green patent filings. However, a significant "Transfer Paradox" persists: while the creation of green knowledge has accelerated, the actual rate of technology transfer from laboratories to industrial applications remains sluggish (Pan et al., 2025). This disconnect suggests that the bottleneck in the green transition lies not in the creation of technology, but in its market allocation. Specifically, the non-standardized nature of green technologies creates severe market frictions—enterprises struggle to identify suitable solutions amidst a sea of academic patents , while innovators hesitate to trade due to valuation difficulties and liability risks (Rujan, 2025).

Historically, the market relied on human intermediaries—such as technology brokers and agencies—to bridge these information and trust gaps. While these intermediaries have played a vital role, their efficacy is increasingly constrained by the inherent limitations of "bounded rationality" and limited service radii. In the face of massive, fragmented, and cross-disciplinary technical data, traditional labor-intensive intermediation suffers from high search costs, low matching precision, and significant agency problems (Albats et al., 2025). Consequently, the green technology market often fails to clear efficiently, leaving valuable low-carbon solutions dormant in the "Valley of Death." This persistent inefficiency raises a critical question: Is there a structural mechanism capable of resolving these frictions more effectively than the traditional human-centric model?

The emergence of the digital economy offers a potential disruption to this stalemate. With data officially recognized as a critical factor of production, digital technologies such as Artificial Intelligence (AI) and Blockchain are reshaping market topologies across various sectors (Anaïs, 2023). However, while existing literature has extensively examined the impact of digitalization on standardized markets like FinTech or E-commerce, the intersection of digitalization and the highly complex green technology market remains underexplored. Current research largely focuses on macro-policy incentives or the digital transformation of individual firms, failing to theoretically articulate the micro-mechanisms of how data elements substitute specific human functions in the technology transfer process. A key theoretical gap remains: Does the introduction of data elements merely "optimize" existing tools, or does it fundamentally "disintermediate" the market structure?

To really get at this gap, we took our investigation to Zhejiang, China—a region that is, frankly, a global pioneer in digital reform. We looked specifically at two emerging practices: the AI-based "Zhizhe" Model and the blockchain-based "Anxinwu" Platform. Our goal was to decode the so-called "Black Box" of data-driven transfer. We didn"t want to view these technologies in isolation, as is often done. Instead, we propose a "Dual-Drive Framework." This helps investigate how different types of data can mitigate search frictions (ex-ante) and trust frictions (ex-post) at the same time. It led us to identify the phenomenon of "Functional Disintermediation." It also became clear that "Techno-Institutional Co-evolution" is a necessity.

This study seeks to provide a new lens for understanding market transformation, offering implications that are actually actionable for policymakers in emerging economies.

## 2.Theoretical Background and Analytical Framework

### *2.1 Transaction Cost Theory in Green Technology Transfer*

ransaction Cost Theory (TCT), as foundationalized by Coase and expanded by Williamson, posits that the efficiency of economic exchange is determined by the friction costs of transacting—namely search, bargaining, and enforcement costs (Avdasheva & Geliskhanov, 2025; Ahmed & Kowalkowski, 2025). In the context of green technology transfer, these costs are exacerbated by two inherent characteristics.

The primary hurdle is the sheer scale of information asymmetry. Green technologies aren"t like standardized commodities you can just pick off a shelf; they involve a lot of complex, tacit knowledge that is surprisingly hard to codify. For potential buyers, this creates a real headache: significant "search costs" to find the right tech and "measurement costs" to figure out if it actually helps the environment. It ends up creating a classic "Lemon Market" dilemma where the high-quality stuff gets undervalued (Zhang & Song, 2025).

Compounding this is the issue of asset specificity and a lingering trust deficit. Since green tech often needs specific complementary assets—think specialized equipment or highly trained personnel—it gets complicated. There is a genuine fear of opportunistic behavior, whether it"s the "hold-up problem" or just plain "greenwashing", which drives up contracting and enforcement costs. We've traditionally relied on human intermediaries to bridge these gaps, but frankly, that often just introduces extra agency costs and efficiency losses (Howells, 2024; Allen et al., 2025; Astous et al., 2024).

### *2.2 Mechanisms of Data-Driven Disintermediation*

The emergence of data as a key factor of production offers a novel pathway to mitigate the aforementioned transaction costs, leading to a structural shift towards "disintermediation" (Mukhopadhyay & Bouwman, 2019). This study identifies two primary mechanisms through which data elements reconstruct the transfer process:

Consider the algorithmic matching mechanism first. Its main job is to aggregate scattered supply and demand info using big data and AI, but the way it does this is quite clever. Algorithms convert messy, unstructured technical descriptions into clean structured vectors, allowing for precise semantic matching (Brynjolfsson, 2017). This basically shifts the entire discovery process from the "bounded rationality" of manual human search to "computational intelligence", significantly lowering the marginal cost of hunting for potential partners (Jia & Chen, 2025).

Then you have the digital trust mechanism, which is all about reducing enforcement costs. Through blockchain and distributed ledgers, we can establish a "trustless trust" environment (Casino et al., 2019). Since transaction histories and IP rights are recorded on an immutable ledger, the data itself serves as undeniable "proof of existence" and "proof of value" (Ansari & Zade, 2025). This reduces the need to rely on third-party verification—which is often slow and expensive—and subsequently lowers the institutional costs associated with monitoring contracts.

First, algorithmic matching mechanism (reducing search costs): digital platforms utilize big data and artificial intelligence (AI) to aggregate fragmented supply and demand information. By converting unstructured technical descriptions into structured data vectors, algorithms can achieve precise semantic matching. This mechanism shifts the discovery process from "bounded rationality" (human search) to "computational intelligence," significantly lowering the marginal cost of searching for potential partners.

Second, digital trust mechanism (reducing enforcement costs): blockchain and distributed ledger technologies create a "trustless trust" environment (Casino et al., 2019). By recording transaction histories, intellectual property rights, and performance data on an immutable ledger, data elements serve as an objective "proof of existence" and "proof of value". This reduces the reliance on third-party verification and lowers the institutional costs associated with contract enforcement and monitoring (Cong & He, 2019).

### *2.3 Conceptual Framework: A Dual-Drive Mechanism*

Synthesizing the Transaction Cost Theory and the digital mechanisms discussed above, this study constructs a "Data-Driven Dual-Drive Disintermediation Framework" (as illustrated in Figure 1). The framework operates as a systemic input-process-output model:

Input Layer: data elementaggregation. The foundation of the framework lies in the granular inputs of heterogeneous data (Ren et al., 2025). It integrates Patent Data (supply-side technical details), Corporate Operational Data (demand-side production needs), and Policy/Regulatory Data (institutional context). These data elements provide the necessary "fuel" for the subsequent de-intermediation process.

Process Layer: the dual mechanisms. This is the core engine where transaction costs are structurally reduced through two parallel paths. The first track, Path A, focuses on AI-Enabled Matching to address ex-ante hurdles. Instead of simple queries, it deploys Large Language Models (LLMs) to directly attack Search Costs. By transforming unstructured technical knowledge into clean, structured vectors, this path effectively solves the "discovery problem" and achieves a high level of Matching Efficiency (Silva & Barbosa, 2024; Rossi, 2024). Running parallel to this is Path B, or Blockchain-Enabled Verification. This track tackles ex-post Trust Costs by utilizing distributed ledger technology. It guarantees that data remains immutable and contracts reliable, thereby solving the "verification problem" without forcing participants to lean on traditional reputational intermediaries.

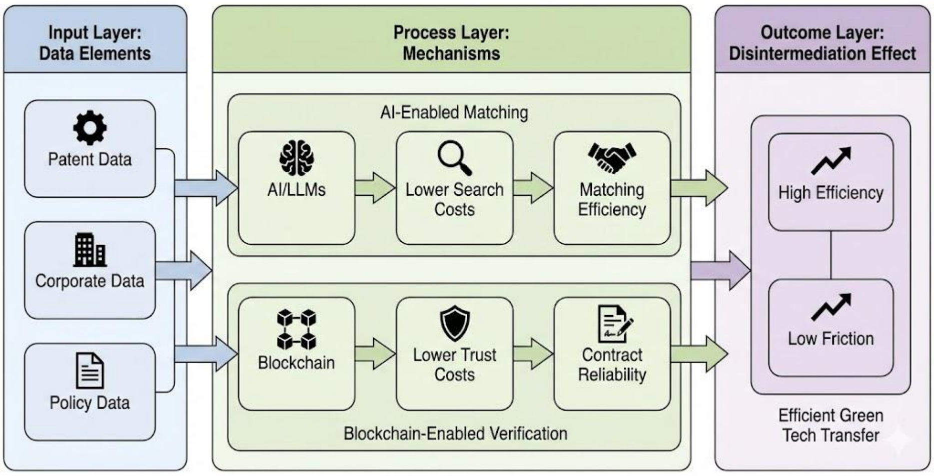
Outcome Layer: structural disintermediation. The synergy of the above mechanisms results in a Disintermediation Effect, characterized by High Efficiency (shortened cycle time) and Low Friction (reduced negotiation obstacles). Ultimately, this leads to an optimized ecosystem for Efficient Green Technology Transfer.

## 3.Research Design and Methodology

### *3.1 Methodological Approach: Qualitative Case Study*

Given the exploratory nature of the research inquiry, this study adopts a qualitative case study methodology. This approach is deemed most appropriate for two primary reasons. First, the integration of generative AI and blockchain into government-led technology markets is a nascent phenomenon (Benbasat et al., 1987). Quantitative data on such emerging practices are currently scarce, rendering large-sample statistical analysis premature (Langley & Abdallah, 2015). Second, the process of "disintermediation" is deeply embedded in a complex institutional context A case study design allows for a holistic investigation of the "how" and "why" mechanisms, capturing the intricate interplay between technological affordances and institutional reforms.

Figure 1: The Conceptual Framework of Data-Driven Disintermediation




*3.2 Case Selection: Purposive Sampling*

This study follows the logic of purposive sampling, selecting Zhejiang Province, China, as the research setting. As the pioneer of China"s "Digital Reform," Zhejiang offers a unique "revelatory case" to observe the frontier of digital transformation.

Within this context, two embedded units of analysis were selected to construct a comparative case design:

Case A: The "Zhizhe" Model 1.0 (Hangzhou). Launched in March 2024 by the Hangzhou Technology Transfer Center, this is China"s first vertical Large Language Model (LLM) dedicated to technology transfer. It represents the mechanism of AI-driven semantic matching (Ex-ante Search Cost Reduction).

Case B: The "Anxinwu" Scenario Application (Zhejiang). Launched in June 2022 by the Zhejiang Provincial Department of Science and Technology. It represents the mechanism of Digital Process Re-engineering (Ex-post Trust Cost Reduction) by integrating state-owned asset management with technology trading systems.

*3.3 Data Collection and Triangulation*

To ensure construct validity and mitigate single-source bias, this study employed a data triangulation strategy. Evidence was curated from three distinct sources (see Table 1).

| Data Type | Specific Documents/Sources | Specific Documents/Sources |
|---|---|---|
| Policy & Archival Records | Notice on the Launch of "Anxinwu" Application issued by Zhejiang Dept. of S&T and Dept. of Finance; Action Plan for "First Choice Place" of Tech Transfer (Hangzhou). | Institutional context; "Safe Harbor" policy logic; Integration with "State-owned Asset Cloud". |
| Technical Specifications | 1."Zhizhe" Model 1.0 Release Report: Details on the integration of 800,000+ sci-tech achievements and demand portraits of 25,000 high-tech enterprises.<br>2."Anxinwu" Operational Guidelines: Flowcharts of the 5 core online functions (Application, Approval, Registration, etc.). | Algorithmic logic (Demand Portrait Construction); Process flow of "Data running instead of legs running" |
| Media & Third-party Reports | n-depth coverage from Science and Technology Daily and Zhejiang Daily; Interviews with officials from Hangzhou Tech Transfer Center. | Validation of outcomes: "100+ successful matches" by Zhizhe in pilot phase; "Real-time senseless supervision" mechanism. |

Table 1. Typology of Data Sources

## 4.Case Description and Mechanism Analysis

### *4.1 Case Context Description*

#### *4.1.1 Case A: The "Zhizhe" Model (Hangzhou) (Focus: AI-driven Supply-Demand Matching)*

The "Zhizhe" (Wise Man) Model, launched in March 2024 by the Hangzhou Technology Transfer Center, represents China"s pioneering effort to integrate Large Language Models (LLMs) into the technology market. Unlike traditional platforms that rely on static database queries, "Zhizhe" is built upon a pre-trained vertical model specifically fine-tuned for the domain of technology transfer.

Technically, the system integrates a vast corpus of heterogeneous data, including 10 billion global patent records, 750 million academic papers, and the operational data of over 25,000 high-tech enterprises in the region. Its core function acts as a "computational bridge." On the demand side, it parses enterprise bidding documents, recruitment notices, and annual reports to construct dynamic "Technological Gene Portraits." On the supply side, it assesses the Technology Readiness Level (TRL) of laboratory patents. By employing high-dimensional vector alignment, the model pushes personalized technology recommendations to enterprises. During its pilot phase alone, the model successfully facilitated over 100 precise matches, significantly outperforming manual brokerage in terms of response speed.

#### *4.1.2 Case B: The "Anxinwu" Platform (Zhejiang) (Focus: Blockchain-driven Institutional Innovation)*

The "Anxinwu" (Safe House) scenario application, initiated in June 2022 by the Zhejiang Provincial Department of Science and Technology, is a systemic reform aimed at the "institutional friction" in transferring state-owned technological assets. It addresses the critical pain point where university researchers fear liability risks (e.g., accusations of underselling state assets) during the transfer process.

The platform functions as a digital ecosystem that connects the "State-owned Asset Cloud," the "Intellectual Property Exchange," and university administrative systems. Its distinct feature is the "Full-Process Digital Chain." Utilizing consortium blockchain technology, "Anxinwu" automatically records every transactional node—from asset valuation and public listing to contract signing. Crucially, it embeds the policy of "Due Diligence Exemption" into its algorithm. Once a transaction workflow creates a complete digital evidence chain (generating a "Green Code"), the system automatically certifies procedural compliance. To date, the platform covers over 250 universities and research institutes, managing a pool of nearly 800,000 scientific achievements, effectively creating a "digital safe harbor" for researchers.

*4.2 Mechanism Analysis: Decoupling Transaction Costs via Data Elements*

Drawing upon the "Dual-Drive Framework," this section dissects the specific pathways through which data elements intervene in the transaction process. We argue that data elements do not merely improve efficiency but fundamentally alter the topology of the green technology market.

*4.2.1 Reconfiguring the Search Mechanism: From "Bounded Rationality" to "Computational Intelligence"*

The first major friction in green technology transfer is the Ex-ante Search Cost, rooted in the "Bounded Rationality" of human agents. In traditional markets, the knowledge of green technologies (e.g., carbon capture materials) is highly tacit and fragmented. Human intermediaries, limited by their cognitive capacity, rely on keyword matching (e.g., searching for "sewage treatment"), which often leads to the "Vocabulary Mismatch Problem." A chemical plant might need a "catalytic oxidation" solution but fails to find it because the patent is described in purely academic terms.

Case A (The "Zhizhe" Model) overcomes this barrier through a mechanism of "Deep Semantic Translation." Unlike simple database queries, the LLM-based system performs a high-dimensional vectorization of both supply and demand.

Step 1: Tacit Knowledge Codification. The model ingests unstructured text from 750 million academic papers and uses Natural Language Processing (NLP) to extract "Technological Features" (e.g., application scenarios, reaction conditions). It translates "Scientific Language" into "Industrial Language."

Step 2: Multidimensional Vector Alignment. The algorithm maps the demand of enterprises (e.g., their pollution discharge data, energy consumption patterns) and the supply of patents into the same vector space. A successful match is no longer defined by keyword identity but by "Vector Proximity."

Step 3: Iterative Reinforcement. Through Reinforcement Learning from Human Feedback (RLHF), the system learns from every click and rejection. This creates a positive feedback loop: as the data volume grows, the search cost marginally decreases towards zero.

This process effectively replaces the "Cognitive Search" of human intermediaries with "Computational Search," resolving the information asymmetry caused by semantic barriers.

*4.2.2 Reconstructing the Trust Mechanism: From "Reputational Trust" to "Algorithmic Enforcement"*

The second friction is the Ex-post Enforcement Cost, specifically the "Institutional Trust Deficit" in transferring state-owned assets. In the Chinese context, the transfer of university patents is often stalled by the "Principal-Agent Problem." University administrators (Agents), fearing ex-post accountability audits for underselling state assets, tend to choose "inaction" over "risky transfer." Traditional solutions rely on heavy bureaucratic endorsements (stamps and approvals), which creates lengthy latency.

Case B (The "Anxinwu" Platform) reconstructs trust through a mechanism of "Algorithmic Safe Harbor."

Step 1: Evidence Chain Locking. By utilizing consortium blockchain technology, the platform creates a "Digital Twin" of the entire transfer process. Every critical action—pricing valuation, public listing, and contract negotiation—is hashed and anchored on the blockchain. This ensures that the transaction history is tamper-proof and traceable, providing an objective "Proof of Existence."

Step 2: Rule-Based Immunity. The most innovative mechanism is the embedding of institutional rules into smart contracts. The system defines the parameters of "Due Diligence" as executable code. When a researcher follows the standard procedure, the system automatically generates a "Green Code." This code serves as legal proof of compliance, triggering an automatic exemption from liability.

Step 3: De-personalized Verification. Trust is no longer derived from the reputation of an intermediary or the authority of a bureaucrat, but from the determinism of the code.

This creates a "Trustless Trust" environment. It decouples the transaction from human subjectivity, allowing the "Institutional Transaction Cost" to be minimized through automation. The reduction of the transaction cycle from 58 days to 30 days is the direct empirical manifestation of this mechanism.

*4.3 Key Findings*

Based on the cross-case synthesis and the mechanism analysis above, this study yields three critical findings that contribute to the theoretical understanding of digital innovation in technology markets.

The empirical evidence actually pushes back against the utopian prediction of total disintermediation, revealing instead a much more nuanced reality we call "Functional Disintermediation". It turns out that introducing data elements doesn"t simply eliminate the need for intermediation; rather, it fundamentally reconfigures the market"s division of labor. What the "Zhizhe" and "Anxinwu" cases really show is that routine, rule-based functions—like information gathering and preliminary matching—have been successfully taken over by AI and blockchain. But this isn"t the end of the human agent. Instead, we are seeing a structural shift from a "Human-Intermediated Market" to a "Platform-Intermediated Market," where humans are displaced from low-value processing but are desperately needed for high-value activities like complex valuation and strategic negotiation. So, digitization isn"t about the extinction of the intermediary, but its evolution.

Crucially, the study also uncovers a synergistic relationship between search and trust, hinting at a "Threshold Effect" in digital transformation. We observed that neither AI-driven search (Case A) nor Blockchain-driven verification (Case B) is sufficient on its own to fix the market failure. Think of the "Zhizhe" model as providing "Visibility" (helping users find tech), while the "Anxinwu" platform provides "Convertibility" (helping users dare to trade). The reality is that efficient search only translates into real deals when trust costs drop below a critical threshold. This implies that platforms need a holistic design: focusing only on matching while ignoring institutional trust risks—or the other way around—is likely to lead to a "liquidity trap," where users either can"t find partners or are simply too afraid to close the deal.

Finally, and perhaps most importantly, the analysis highlights that institutional innovation is a prerequisite for technological efficacy, pointing to a dynamic of "Techno-Institutional Co-evolution." A recurring theme in the "Anxinwu" case is that the blockchain ledger would have been functionally inert—essentially a digital paperweight—without parallel regulatory reform. The turning point wasn"t just deploying the smart contract code; it was the government"s legal recognition of that code as valid evidence for "Due Diligence Exemption." This offers a profound lesson for developing economies: technology is not a magic wand that automatically corrects market frictions. The efficacy of digital infrastructure is strictly contingent on the adaptability of the institutional environment. Investing in fancy algorithms without modernizing the legal protocols is, frankly, unlikely to yield sustainable improvements.

## 5.Conclusion and Implications

### *5.1 Research Conclusion*

This study set out to explore how data elements reconstruct the mechanism of green technology transfer. Through an exploratory dual-case study of the "Zhizhe" Model and "Anxinwu" Platform in Zhejiang, China, we draw the following conclusions: First, the inherent friction in green technology transfer stems from high Ex-ante Search Costs (due to cognitive gaps) and high Ex-post Trust Costs (due to institutional liability). Second, data elements intervene in this process through a "Dual-Drive Mechanism." On the supply-demand side, AI-driven semantic alignment substitutes human cognitive search; on the institutional side, blockchain-driven evidence chains substitute bureaucratic verification. Third, this substitution leads to "Functional Disintermediation." While human intermediaries are not entirely eliminated, their core functions of matching and validation are effectively decoupled from labor-intensive processes, resulting in a significant gain in transaction efficiency.

### *5.2 Theoretical Contributions*

This study contributes to the literature on innovation management and digital economics in two ways:

First, extending Transaction Cost Theory to the Digital Context: Previous TCT research largely focused on organizational structures (market vs. hierarchy). This study introduces "Data Elements" as a critical variable, proving that the marginal cost of market transactions can be lowered solely by technological architecture, without changing the ownership structure.

Second, clarifying the "Disintermediation" Debate: Existing literature oscillates between "Disintermediation" and "Re-intermediation." Our finding of "Functional Disintermediation" offers a nuanced reconciliation: the market is evolving towards a hybrid state where processes are disintermediated by algorithms, but strategic decisions remain human-mediated. This provides a precise theoretical definition for the digitization of technology markets.

### *5.3 Policy and Managerial Implications*

For policymakers and practitioners, particularly in emerging economies, this study offers actionable insights:

For Governments (Institutional Design): Investing in digital infrastructure (servers) is insufficient without "Institutional Compatibility." Governments must legally recognize the validity of digital proofs (e.g., smart contract logs) to enable the "Due Diligence Exemption." Without this legal backing, the technology remains a "toy" rather than a "tool."

For Platform Builders (System Integration): A successful platform must address the "Search-Trust" duality simultaneously. Building a matchmaking engine without a verification module (or vice versa) will likely lead to market failure. Platforms should aim for "Full-Link Digitization" rather than fragmented solutions.

For Enterprises (Digital Readiness): Enterprises must actively digitize their operational data (e.g., energy consumption records). In the AI era, data is the "currency" to purchase visibility in the technology market.

### *5.4 Limitations and Future Research*

Honesty about limitations strengthens the validity of the study. First, as a single-context study based in Zhejiang (a digitally advanced region), the findings may have boundary conditions when applied to less developed regions with weaker digital infrastructure. Future research could conduct comparative studies in different institutional contexts. Second, due to the nascent nature of the phenomenon, this study is qualitative. Future scholars are encouraged to employ large-sample quantitative methods (e.g., Difference-in-Differences models) to empirically measure the precise impact of these platforms on regional innovation efficiency once more longitudinal data becomes available.

## AUTHOR CONTRIBUTIONS

Guoyin Zhang (1st): Conceptualization: Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing

Rong Li (Corresponding author): Conceptualization, Writing - original draft, Writing - review & editing, Methodology, Investigation, Data collection, Funding acquisition

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**CONFLICT OF INTEREST STATEMENT**

The authors declare that there are no commercial or financial relationships that could be construed as a potential conflict of interest.

**DATA AVAILABILITY STATEMENT**

The data generated and analyzed in this study are available from the corresponding author upon reasonable request. All data will be provided without undue restriction.

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**References**

1. Gan, J. (2025). New insights into how green innovation, renewable energy, and institutional quality shape environmental sustainability in emerging economies. *Frontiers in Environmental Science, 13*, 1525281.
2. Wu, S., Chen, D., & Tang, T. (2026). The impact of technology transfer on green total factor energy efficiency: Evidence from the establishment of national technology transfer centers. *Sustainability, 18*(2), 751-782.
3. Rujan, C. (2025). Who drives green tech? Patenting trends of top R&D firms. *In EconPol Forum* , *26*(4), 82-88.
4. Albats, E., Etzkowitz, H., & Kalthaus, M. (2025). Digital platforms for academia–industry knowledge exchange: Characterisation, functions, and types. *Industry and Innovation, 32*(9), 1059–1080.
5. Anaïs, C. (2023). Environmental impacts of digital technology: 5-year trends and 5G.
6. Avdasheva, S. B., & Geliskhanov, I. Z. (2025). Transaction cost economics: Lessons from past reforms and potential for the digital economy. *Russian Journal of Economics, 11*(3), 237-268.
7. Ahmed, T., & Kowalkowski, C. (2025). The new industry playbook: digital service innovation in multi-platform ecosystems. *Journal of Enterprise Information Management*. Advance online publication.
8. Zhang, L., & Song, Z. (2025). Digital transformation, green technology innovation and corporate value. *Frontiers in Environmental Science, 13*, 1485881.
9. Howells, J. (2024). Innovation intermediaries in a digital paradigm: A theoretical perspective. *Technovation, 129*, 102889.
10. Allen, J., Clark, R., Houde, J. F., Li, S., & Trubnikova, A. (2025). The role of intermediaries in selection markets: Evidence from mortgage lending. *The Review of Financial Studies, 38*(11), 3284–3328.
11. Astous, P., Gemmo, I., & Michaud, P. C. (2024). The quality of financial advice: What influences recommendations to clients? *Journal of Banking & Finance, 169*, 107291.
12. Mukhopadhyay, S., & Bouwman, H. (2019). Orchestration and governance in digital platform ecosystems:

a literature review and trends. *Digital Policy, Regulation and Governance, 21*(4), 329-351.
13. Brynjolfsson, E., Rock, D., & Syverson, C. (2017). *Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics* (No. w24001). National Bureau of Economic Research.
14. Jia, K., & Chen, Y. (2025). Research on the Impact of Data Factors on Enterprise Green Innovation—Evidence from Chinese Manufacturing Enterprises. *Sustainability, 17*(5), 2184.
15. Casino, F., Dasaklis, T. K., & Patsakis, C. (2019). A systematic literature review of blockchain-based applications: Current status, classification and open issues. *Telematics and informatics, 36*, 55-81.
16. Ansari, S. Z., & Zade, S. D. (2025). Blockchain-Enabled Digital Timestamping and Consensus-Based Incentivization for Collaborative Intellectual Property Management. *Ingenierie des Systemes d'Information, 30*(11), 3077.
17. Cong, L. W., & He, Z. (2019). Blockchain disruption and smart contracts. *The Review of Financial Studies, 32*(5), 1754-1797.
18. Ren, J., Wang, M., Li, X., & Ding, X. (2025). Data Elements and Agricultural Green Total Factor Productivity: Evidence from a Quasi-Natural Experiment Based on Public Data Openness in China. *Agriculture, 15*(11), 1130.
19. Silva, L., & Barbosa, L. (2024). Improving dense retrieval models with LLM augmented data for dataset search. *Knowledge-based systems, 294*, 111740.
20. Rossi, N., Lin, J., Liu, F., Yang, Z., Lee, T., Magnani, A., & Liao, C. (2024). Relevance filtering for embedding-based retrieval. *In Proceedings of the 33rd ACM International Conference on Information and Knowledge Management* (pp. 4828-4835).
21. Benbasat, I., Goldstein, D. K., & Mead, M. (1987). The case research strategy in studies of information systems. *MIS quarterly*, 369-386.
22. Langley, A., & Abdallah, C. (2015). Templates and turns in qualitative studies of strategy and management. *In Research methods for strategic management* (pp. 137-166). Routledge.