Agricultural AI Value Capture: From Constraint Removal to Repeatable Deployment

Johnny Kao

Independent Researcher, Tokyo, Japan

ORCID: 0009-0004-1446-6001

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Abstract

Agricultural artificial intelligence can create substantial operational value without producing an equally strong technology business. A robot may reduce a scarce task, a decision system may improve reliability, or an autonomous system may expand feasible production, yet the supplier can still fail to identify the right payer, overcome adoption friction, deploy repeatably, or retain enough of the created value to sustain the offering. This paper develops an Agricultural AI Value-Capture framework that treats commercialization as a linked sequence from technology to constraint removal, economic value, buyer identification, adoption, deployment, and value capture.

The framework is positioned against recent research on digital-agriculture adoption, interoperability, platformization, servitization, market power, and business-model innovation. Existing work establishes that value creation and value capture are distinct, that profitability and technical support shape adoption, and that digital agriculture increasingly relies on service- and platform-based models. The contribution here is narrower and operational: it makes deployment an explicit strategic link between adoption and capture, defines Deployment Replicability as the ability to reproduce a stable solution with bounded site-specific adaptation, and introduces Buyer-Value Alignment and Value-Capture Leakage as diagnostic concepts for agricultural AI businesses.

The framework implies that superior AI is neither necessary nor sufficient for a scalable agricultural technology business. Stronger positions arise when a technology removes a binding constraint for an identifiable payer, creates value large enough to justify operational disruption, enters heterogeneous farms through a repeatable deployment system, and retains an economically viable share of the value after service, financing, competition, and ecosystem effects. The central claim is that agricultural AI should be evaluated not only by what it can technically accomplish, but by whether the path from constraint removal to repeatable value capture remains intact.

Keywords: artificial intelligence; agriculture; AgTech; business models; value capture; technology adoption; deployment; digital agriculture

1. Introduction

Agricultural AI is often evaluated at the level of technical performance: accuracy, autonomy, yield response, labor savings, or the ability to control a production variable. Those measures matter, but they do not answer a basic commercial question. If a technology creates value on a farm, what must happen before a technology provider can build a repeatable business around that value?

The distinction is important because agriculture is a physical, heterogeneous, and seasonal operating environment. A farm is not an empty software workspace. Equipment differs across sites, biological conditions change, connectivity is uneven, staff must learn new workflows, and service failures can arrive during narrow production windows. A technically successful product can therefore face commercial failure at several points after the underlying model or machine has already proved that it works.

Recent literature increasingly recognizes this broader problem. Digital-agriculture research identifies perceived profitability, infrastructure, technical knowledge, reliability, compatibility, and support as determinants of adoption (Dibbern et al., 2024; Kroupova et al., 2025). Business-model research shows a shift from one-time product sales toward subscriptions, pay-per-use, services, platforms, and outcome-oriented arrangements (Bouncken & Cesinger, 2026; Florez et al., 2026). Agricultural value-chain research further shows that value creation and value capture can be distributed unevenly across farmers, technology providers, platforms, and downstream actors (Klingenberg et al., 2022; Awada & Phillips, 2023).

This paper develops the Agricultural AI Value-Capture framework by formalizing the constraint-to-business logic introduced in Kao (2026a). It also connects that logic to the Agricultural Viability Frontier, which distinguishes technologies that improve already viable production from those that change what production is economically feasible (Kao, 2026b), and to Profitable Control, which emphasizes that technically available control must still justify its economic burden (Kao, 2026c). The present paper asks a different question: once a technology creates agricultural value, under what conditions can a provider repeatedly reach the buyer and retain enough of that value to sustain a business?

The answer is organized around four concepts: the Agricultural AI Value-Capture Chain, Buyer-Value Alignment, Deployment Replicability, and Value-Capture Leakage. Together they shift analysis away from the vague question of whether an AI product is useful and toward a sequence of commercially necessary conditions. The framework is diagnostic rather than predictive. It does not rank business models or claim that one organizational form is universally superior.

2. Related Literature and the Gap

Business-model theory has long distinguished value creation, value delivery, and value capture. Teece (2010) describes a business model as the architecture through which a firm delivers value, induces payment, and converts that payment into profit. In digital agriculture, this separation is especially important because the actor creating a technical improvement may not be the actor that captures most of its economic value.

Klingenberg et al. (2022) show that digitalization changes activities, flows, actors, and governance across the agricultural value chain, while value capture depends on competitive dynamics and institutional conditions. Birner et al. (2021) similarly emphasize that the supply side of digital agriculture includes incumbent agribusiness firms, software companies, and start-ups, creating opportunities alongside concerns about concentration and market power. Klerkx et al. (2019) situate economics, management, ownership, power, skills, and adoption within the broader social-science agenda of digital agriculture.

More recent work moves closer to the present problem. Kerstens et al. (2025), studying nine digitally enabled agri-food cases, develop a typology of value-capture models and connect initial capture choices to the ability to scale participation. Galgo et al. (2026) find that climate-smart agricultural practices can improve value creation and delivery while leaving value capture unresolved. Florez et al. (2026), analyzing 170 AgTech start-ups, identify pay-per-use, subscriptions, freemium arrangements, and other solution patterns that change how firms monetize digital agricultural offerings. Bouncken and Cesinger (2026) likewise describe Agriculture 4.0 as a shift toward service-oriented and platform-mediated forms of value creation, delivery, and capture.

Adoption research adds a second stream. Dibbern et al. (2024) identify economic conditions, infrastructure, technical knowledge, organizational characteristics, reliability, security, and privacy as major adoption factors. Kroupova et al. (2025) find that perceived economic benefit, technical literacy, expert advice, and technical support are prominent determinants of precision-agriculture adoption. Munz et al. (2024) show that low adoption can reflect technology-specific economic limits and that service-oriented private-sector mechanisms can improve adoption in some cases. Cisternas et al. (2020) demonstrate the breadth of precision-agriculture implementation choices while noting the absence, in their review, of a general tool for deciding which technology to implement in a given crop context.

A third stream concerns interoperability and lock-in. Roussaki et al. (2023) demonstrate the practical need to integrate heterogeneous devices, platforms, and data resources in smart agriculture. Urdu et al. (2024) compare interoperability architectures across major European agri-food projects and identify interoperability as a high-priority challenge for platform use. Hackfort (2023) shows that technological, data, legal, and other lock-ins can shape farmer dependence, while Awada and Phillips (2023) model how market power affects the distribution of gains from smart-farming services.

These literatures establish most of the ingredients required for a commercialization framework, but they are often analyzed separately: business-model configuration, farmer adoption, platform governance, market power, and interoperability. The narrower gap addressed here is the lack of a compact constraint-first sequence that makes deployment a distinct strategic link between adoption and capture. In agriculture, a customer can agree that a product is useful and even decide to adopt it, yet the provider can still fail to deploy it economically across heterogeneous sites. Treating deployment as a separate link is therefore central to the contribution of this paper.

3. From Technology to Constraint Removal

The first discipline is to begin with the production constraint rather than the AI capability. A model can be sophisticated and still attack a problem too small, too infrequent, or too weakly connected to farm economics to support a durable business. The relevant unit is therefore not the algorithm alone but the constraint that the technology changes.

A constraint is commercially important when it limits a decision the farm already has reason to make. Examples include a recurring labor task whose staffing is unreliable, an expertise bottleneck that limits the number of sites a manager can supervise, an input-management problem with material cost exposure, or an operating risk that prevents expansion. This logic is consistent with the Agricultural Viability Frontier: removing a binding constraint can change a production decision rather than merely improve a margin (Kao, 2026b).

The distinction also guards against percentage-based reasoning. A 20 percent improvement in a small cost category may create less economic value than a 5 percent improvement in a large, binding category. Likewise, a technically impressive improvement may create little buyer value if existing alternatives already solve the problem cheaply. The correct starting point is therefore the economic baseline: what happens without the technology, what constraint remains binding, and how much does relieving it change the buyer's feasible choices?

Definition 1 - Constraint Removal Value. Constraint Removal Value is the economic value generated because a technology weakens or removes a specific constraint that limits agricultural performance, continuity, scale, reliability, or viability. It is distinct from technical performance itself.

4. The Agricultural AI Value-Capture Chain

The book source expresses the commercialization problem as a seven-link chain: Technology -> Constraint -> Economic Value -> Buyer -> Adoption -> Deployment -> Value Capture (Kao, 2026a). The sequence is intentionally demanding. A weak link can prevent a technically sound product from becoming a repeatable business.

Definition 2 - Agricultural AI Value-Capture Chain. The Agricultural AI Value-Capture Chain is the sequence through which a technical capability must (1) change a meaningful constraint, (2) create economic value, (3) connect that value to an identifiable payer, (4) survive the payer's adoption threshold, (5) be deployed repeatedly in operating farms, and (6) leave the provider with sufficient retained value after delivery costs and market effects.

The sequence should not be interpreted as a rigid project-management waterfall. Several links are discovered iteratively. A provider may learn during deployment that the true buyer is not the farm operator but a processor, cooperative, equipment dealer, insurer, or financing partner. A pilot may reveal that integration cost destroys the apparent economics. A pricing experiment may reveal that the party receiving the largest benefit does not control the purchasing decision. The value of the chain is diagnostic: it forces those failure points to be made explicit.

The distinction between economic value and value capture is especially important. A provider can create large value for the agricultural system and still capture little of it. Competition can reduce price. Hardware financing can absorb margin. Installation and service can consume revenue. Downstream buyers can appropriate part of the gain. Market power can also shift gains toward technology providers rather than farmers, as Awada and Phillips (2023) show for data-driven smart-farming services. The chain therefore separates creation from appropriation rather than assuming that one implies the other.

Table 1. The Agricultural AI Value-Capture Chain

Chain link	Key question	Typical failure mode
Technology	Does the capability work reliably in the operating environment?	Demo performance does not survive field conditions.
Constraint	Does it change a problem that materially limits the operation?	Product improves a non-binding or low-value variable.
Economic value	How much value is created in money, risk reduction, continuity, or feasible scale?	Percentage improvement is economically small.
Buyer	Who receives enough benefit and controls a budget?	Beneficiary and payer are different actors.
Adoption	Is the surplus large enough to justify switching, learning, and uncertainty?	Positive ROI is overwhelmed by implementation friction.
Deployment	Can the solution be reproduced across heterogeneous sites?	Each customer becomes a new integration project.
Value capture	Does enough value remain after price pressure and delivery costs?	Revenue grows while service, capital, and support consume margin.

5. Buyer-Value Alignment

The obvious buyer for agricultural technology is often assumed to be the farmer because the technology operates on the farm. That assumption is frequently useful but not universally correct. Reliability, traceability, quality consistency, and supply predictability can create value for processors, retailers, lenders, insurers, equipment dealers, and other actors. Klingenberg et al. (2022) show that digitalization changes both actors and governance across agricultural value chains, while Bustamante (2023) demonstrates that agricultural platforms can be evaluated through competing constructions of economic and broader social value.

> **Definition 3 - Buyer-Value Alignment. Buyer-Value Alignment exists when the actor asked to pay has sufficient control over the purchase decision and receives, or can appropriate, enough of the technology's economic benefit to justify payment and organizational change.**

Misalignment can occur in several ways. The farmer may create data that improves a platform while capturing little of the resulting value. A retailer may benefit from more reliable supply while the farm bears the technology cost. A lender may benefit from reduced production risk but have no mechanism to subsidize the technology. Conversely, a technology provider with strong platform or data power may capture a disproportionate share of gains, weakening the buyer's incentive to adopt (Awada & Phillips, 2023).

Buyer-Value Alignment therefore concerns more than willingness to pay. It includes bargaining power, contract structure, budget ownership, timing of benefits, and who bears downside risk. Galgo et al. (2026) provide an agricultural example of why this matters: value creation and delivery can improve without an equally resolved capture mechanism. A commercially viable design must connect the value to a payer with both motivation and authority.

6. Adoption Is Necessary but Not Sufficient

Even when the payer is clear, adoption imposes a threshold. Farms already have operating systems: equipment, schedules, workers, agronomic routines, seasonal deadlines, financing constraints, and accumulated local knowledge. A new technology must therefore outperform not only the current technical solution but also the disruption required to change it.

The adoption literature strongly supports this broader view. Dibbern et al. (2024) identify economic conditions, infrastructure, technical knowledge, organizational characteristics, reliability, security, and privacy as recurring drivers and barriers. Kroupova et al. (2025) find perceived profitability to be central, but also identify technical literacy, advice, and support as important. Munz et al. (2024) show that adoption potential can remain low when technologies reach farm-level economic limits and that technology-specific interventions are more effective than general expectations that all farms should digitize.

This suggests a practical adoption condition: the perceived benefit must be large enough to compensate not only for purchase price but for learning, workflow change, uncertainty, and switching risk. A modestly positive engineering ROI may therefore be insufficient. The product must create a surplus large enough to survive implementation friction.

This point helps explain why service models can matter. Machinery cooperatives, contractors, dealer networks, subscriptions, and pay-per-use arrangements can convert fixed adoption burdens into variable or supported forms. Florez et al. (2026) find pay-per-use to be a prominent pattern among digital-agriculture start-ups, while Bouncken and Cesinger (2026) describe the broader shift toward service- and platform-based models. These arrangements do not remove the need for value; they change who carries capital, integration, and utilization risk.

7. Deployment Replicability

Adoption answers whether a customer is willing to use a technology. Deployment asks whether the provider can make the technology work inside the customer's physical operation at an economically repeatable cost. In agriculture, these are separate problems.

> **Definition 4 - Deployment Replicability. Deployment Replicability is the ability to reproduce a stable agricultural technology offering across additional sites while keeping site-specific engineering, integration, training, service, and support burdens within bounded and economically manageable limits. Replicability does not require identical farms; it requires a repeatable core plus controlled adaptation.**

This distinction is particularly important for software-heavy agricultural AI. Software can be copied cheaply, but the conditions required for it to operate may not be cheap to reproduce. Sensors must be calibrated. Existing equipment may expose different interfaces. Connectivity varies. Data formats differ. Local agronomic assumptions may need adjustment. Staff require training. Service response must work when production cannot wait.

Interoperability research gives this deployment problem a concrete technical basis. Roussaki et al. (2023) describe the integration of heterogeneous technologies as a central smart-agriculture challenge. Urdu et al. (2024) similarly identify semantic and technical interoperability as high-priority requirements for agri-food digital platforms. Hackfort (2023) shows that proprietary systems and data arrangements can create lock-in, which may simplify one vendor's ecosystem while increasing switching costs and reducing buyer flexibility.

Deployment Replicability therefore differs from software scalability. A model may run for another user at near-zero compute distribution cost while the farm-facing deployment still requires days or weeks of integration and local service. The commercial test is whether each new customer behaves like a repeatable configuration or a new engineering project.

This also changes the interpretation of field experience. Local deployment knowledge can become a strategic asset because it converts heterogeneity into reusable implementation routines. Standard connectors, integration templates, commissioning procedures, dealer training, remote diagnostics, and clear escalation paths can all increase replicability even when the underlying AI model changes only incrementally.

8. Business-Model Archetypes

Agricultural AI can be delivered through several business-model archetypes. The source book distinguishes selling a tool, selling an intelligence layer, and owning the production system (Kao, 2026a). Recent business-model research supports treating these as different configurations of value creation, delivery, and capture rather than as interchangeable 'AI companies.'

The tool model sells or leases a physical capability into an operating farm. Its advantage is often a clear task baseline: labor, chemicals, fuel, downtime, or another observable cost. Its burden is hardware capital, maintenance, field reliability, and service. The intelligence-layer model adds sensing, analytics, recommendations, or autonomous control to assets the customer already owns. It can carry lower manufacturing burden but faces integration, interoperability, trust, and recurring support costs. The integrated-producer model embeds AI inside a production business and captures value through the crop or agricultural output itself. It may retain more operating upside but also absorbs crop risk, working capital, energy, labor, financing, and market exposure.

No archetype is universally superior. The relevant question is which set of risks a firm must own to access the value it creates. Kerstens et al. (2025) show that value-capture choices affect the ability to scale participants in digitally enabled agri-food models. Florez et al. (2026) identify multiple pricing and solution patterns rather than a single dominant configuration. The constraint-first perspective therefore favors selective ownership: own or control enough of the critical capability to make the value proposition defensible, but do not assume that owning the entire farm is required to capture value.

> **Principle 1 - Constraint-Focused Value Capture. A provider strengthens its commercial position when it controls a capability that relieves a binding agricultural constraint, connects that relief to a motivated payer, and can deliver it repeatedly without assuming unrelated production risks that overwhelm the retained value.**

Table 2. Business-model archetypes for agricultural AI

Archetype	Primary value-capture route	Main strength	Main burden
Tool / embodied system	Sale, lease, pay-per-use, service contract	Clear task baseline and observable physical output	Hardware capital, maintenance, reliability, field service
Intelligence layer	Subscription, license, usage or outcome fee	Can leverage installed equipment and distribute software improvements	Integration, interoperability, data quality, trust, recurring support
Integrated producer	Margin on agricultural output	Potentially captures operational upside directly	Owns crop, market, energy, labor, asset and financing risk

9. Value-Capture Leakage

A final source of confusion is the tendency to equate customer value, provider revenue, and provider profit. They are different quantities. A technology may create one million dollars of annual farm value and still support only a fraction of that amount as price. The provider's retained economics are reduced further by deployment, service, financing, warranty, and support costs.

For a provider, a simple accounting representation is:

$$VendorCapture = Payment - DeploymentCost - ServiceCost - FinancingCost$$

where Payment is the amount received from the buyer and the cost terms represent customer-specific deployment, ongoing service, and financing or capital burden attributable to the offering. This is deliberately not a valuation model; it simply prevents revenue from being mistaken for retained value.

A second diagnostic quantity is the gap between the economic value created for the broader system and the value retained by the provider:

$$CaptureGap = EconomicValueCreated - VendorCapture$$

The gap is not automatically a problem. Some of the created value should remain with the buyer or other participants or the product will not be adopted. The strategic problem appears when the provider's retained share is too small or too costly to sustain continued deployment, support, and innovation.

Several mechanisms produce leakage. Competition can compress price. Dealers or integrators may require margin. Financing can transfer value to capital providers. Downstream buyers can negotiate away part of farm-level gains. Platform governance and market power can redistribute returns across actors (Klingenberg et al., 2022; Awada & Phillips, 2023). Interoperability and switching conditions can also affect bargaining power and long-run capture (Hackfort, 2023; Urdu et al., 2024).

This perspective helps separate two strategic questions: Does the technology create enough value to matter, and can the provider retain enough of that value after the real cost of entering and supporting the farm? Agricultural AI businesses must answer both.

10. Operational Diagnostics and Evidence

The framework can be operationalized as a diagnostic rather than a score. The purpose is to locate the weak link in a commercialization path, not to assign an arbitrary numerical grade.

Evidence from recent studies illustrates the logic. Dibbern et al. (2024) and Kroupova et al. (2025) show why adoption cannot be reduced to technical usefulness. Munz et al. (2024) demonstrates that farm-level economic limits can cap adoption even when the technology category is strategically attractive. Roussaki et al. (2023) and Urdu et al. (2024) show why integration and interoperability can become deployment constraints. Kerstens et al. (2025) and Florez et al. (2026) show that the choice of capture model affects scaling and revenue architecture. Awada and Phillips (2023) show that market power changes the distribution of gains. Together these findings support a chain in which creation, adoption, deployment, and capture must all be examined separately.

Cisternas et al. (2020) also provides an important caution. Precision agriculture contains many technology-crop combinations, and implementation choices remain context dependent. Deployment Replicability should therefore not be interpreted as forcing farms into a single standardized configuration. The goal is a stable product architecture that tolerates known variation without returning to bespoke engineering for every site.

Table 3. Evidence mapped to the framework

Evidence	Observed result	Framework implication
Dibbern et al. (2024); Kroupova et al. (2025)	Profitability, infrastructure, literacy, advice and support shape adoption.	Economic value must survive adoption friction; usefulness alone is insufficient.
Munz et al. (2024)	Some precision technologies face farm-level economic limits; service mechanisms can improve adoption potential.	Pricing and delivery architecture can move the adoption threshold.
Roussaki et al. (2023); Urdu et al. (2024)	Heterogeneous systems require interoperability across devices, data and platforms.	Deployment is a distinct commercial capability, not an automatic consequence of software scalability.

Evidence	Observed result	Framework implication
Kerstens et al. (2025); Florez et al. (2026)	Value-capture models and pricing patterns affect scaling and participation.	Capture architecture should be analyzed together with deployment burden.
Awada & Phillips (2023)	Market power changes how smart-farming gains are distributed.	Value created for the system is not the same as value retained by the farm or vendor.
Hackfort (2023)	Digital agriculture can create technological, data and other lock-ins.	Capture through lock-in may raise switching costs and create ecosystem trade-offs.

11. Research Agenda

The framework suggests several empirical tests. First, researchers can trace agricultural AI deployments longitudinally from pilot to commercial scale and record where projects fail: insufficient constraint value, unclear payer, adoption friction, deployment cost, or weak value retention. This would provide a more granular commercialization failure map than studies that classify outcomes only as adoption or non-adoption.

Second, Deployment Replicability can be measured directly. Candidate variables include installation hours per site, engineering hours, number of custom interfaces, training hours, service incidents, remote versus on-site resolution rates, mean time to commission, mean time to recover, and deployment cost as a share of first-year contract value. The key empirical question is whether these burdens decline, stabilize, or continue to scale roughly one-for-one with each additional customer.

Third, Buyer-Value Alignment can be studied through contract and value-flow analysis. Researchers can estimate which actor receives the operational benefit, which actor owns the budget, who bears downside risk, and how realized gains are split among farmers, vendors, dealers, processors, lenders, insurers, and platform operators. Awada and Phillips (2023) provides a useful precedent for explicitly modeling the distribution of smart-farming gains.

Fourth, business-model archetypes can be compared on deployment economics rather than revenue growth alone. Hardware sales, subscriptions, pay-per-use, outcome-based contracts, and integrated-production models may differ in gross margin, capital intensity, service burden, renewal, switching costs, and risk transfer. Recent start-up and business-model studies provide an empirical base for such comparison (Florez et al., 2026; Kerstens et al., 2025).

Finally, the relationship between interoperability and capture deserves careful study. Open interoperability can lower adoption and deployment friction but may weaken lock-in and supplier bargaining power. Proprietary integration can strengthen capture for an incumbent while raising customer switching costs and ecosystem dependence. Research should therefore distinguish business-model scalability from ecosystem welfare rather than assuming they move together.

12. Limitations

This paper is conceptual and does not empirically calibrate the proposed chain. The framework identifies necessary commercial questions but does not specify universal thresholds for acceptable adoption cost, deployment burden, or provider capture. Those values depend on crop, farm scale, geography, capital structure, production risk, and the availability of substitutes.

The framework also focuses primarily on private economic value. Digital agricultural systems can create or destroy social, environmental, distributional, and strategic value that is not fully priced in a commercial transaction. Bustamante (2023) shows that agricultural platforms can embody competing conceptions of economic and common-good value, while Hackfort (2023) highlights power and dependence created by digital lock-ins. A strong private capture model is therefore not automatically socially desirable.

A further limitation is that buyer and provider boundaries may be fluid. Cooperatives, dealers, integrators, insurers, processors, and public programs can share deployment roles and risks. The framework can represent such arrangements, but empirical work should avoid forcing complex ecosystems into a simple bilateral vendor-farmer contract.

Finally, the framework does not imply that every agricultural AI provider should maximize appropriation. Sustainable value capture requires leaving enough value with adopters and partners to maintain participation, learning, and trust. Excessive capture or restrictive lock-in can undermine the very adoption and ecosystem conditions on which the business depends.

13. Conclusion

Agricultural AI can work technically, create farm-level value, and still fail as a business. The missing steps are often commercial rather than computational: identifying the binding constraint, connecting value to the payer, crossing the adoption threshold, entering heterogeneous farms through a repeatable deployment system, and retaining sufficient value after the costs of delivery and competition.

The Agricultural AI Value-Capture Chain makes those steps explicit. Buyer-Value Alignment asks whether the party paying can actually appropriate enough of the benefit. Deployment Replicability asks whether the solution can be reproduced without turning every customer into a custom engineering project. Value-Capture Leakage separates the economic value created from the amount the provider ultimately retains.

The resulting perspective is deliberately narrower than a general theory of digital-agriculture business models. Existing literature already explains servitization, platformization, adoption, market power, and value capture. The contribution here is to connect those literatures through a constraint-first, deployment-explicit diagnostic tailored to agricultural AI.

The central implication is simple: the strongest agricultural AI business is not necessarily the one with the most advanced model, the most integrated farm, or the largest theoretical value pool. It is the one that can repeatedly remove a constraint that matters, reach the actor with reason and authority to pay, survive the physical realities of deployment, and retain enough of the created value to keep doing it again.

AI Use Disclosure

OpenAI's ChatGPT was used only for literature discovery and bibliographic verification. The author independently reviewed all cited sources and remains solely responsible for the final manuscript, its arguments, source selection, and citations.

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