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Embodied Artificial Intelligence (AI) business model dynamics: concept, framework, and the agriculture template

Ricarda B. Bouncken[1] · **Beate Cesinger**[1]

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Abstract
Embodied Artificial Intelligence (AI) refers to AI systems in which intelligence is embedded in physical systems and emerges through interaction with its environment. Embodied AI (partly referred to as embedded AI also) acts in the real world through continuous cycles of sensing, decision-making, actuation, and learning. Embodied AI participates in operations and moves beyond supporting decision-making-support to a constitutive element of value creation. Firms must redesign what activities are performed, how they are linked, and who controls them. Embodied AI implies a double loop: a closed learning loop inside the adopting firm, where embodied AI transforms situated use into operational feedback and workflow changes, and an external learning loop across the ecosystem of technology providers, component suppliers, software firms, platform orchestrators, and users. Data generated through physical use travels beyond the adopting firm. Our conceptual study provides pioneering theoretical accounts of embodied AI in management research and focuses on its implications for business models. We develop two complementary models. First, a transition model shows how business models shift from asset-based and episodic logics toward adaptive, data-driven systems. Second, an integrative embodied AI business model grid explains how changes are generated through reconfiguration of value activities, interdependencies, and governance across actors and technologies. We derive nine propositions specifying how embodied AI transforms business models. We further show four systemic tensions: Openness versus control, scaling versus local fit, automation ambition versus reliability constraints, and monetization versus trust. Using agriculture as a revealing template, carves out how embodied AI reshapes business models in traditional industries moving from product performance toward continuous workflow optimization, lifecycle-based orchestration, and recurring, trust-based monetization.

Keywords AI · Embodied AI · Embedded AI · Business model innovation · Agritech · Smart farming · Dynamics · Agriculture

Extended author information available on the last page of the article

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1 Introduction

The disruptive potential of digital technologies (Ulrich et al. 2024), particularly machine learning (ML), artificial intelligence (AI), and robotics (Åström et al. 2022; Kanbach et al. 2024) offers significant impetus for business model dynamics and innovation (Bouncken et al. 2021). Business models describe the firm's architecture of creating value, how it delivers the value to customers, and secures revenue from it (Teece 2010). Their architecture of transactions has been structured in the content, structure, and governance (Zott & Amit 2008; 2010). Despite the large emerging research on AI (Chalmers et al. 2026; Spanjol et al. 2024), only scant previous research shed light on how AI can change business models (Bahoo et al. 2023; Burström et al. 2021; Jobstreibizer et al. 2025; Jorzik et al. 2024).

However, very little understanding exists about embodied AI, the integration of AI in physical forms (Chalmers et al. 2026) and none, so far, considers what embodied AI implies for business models. Embodied AI characterizes a new generation of intelligent machinery in which cognition emerges from continuous interaction with the physical environment rather than from abstract data processing alone (Huang 2025; Yifan et al. 2025). It enables machines to autonomously perform in dynamic environments through multimodal sensing and self-supervised learning (Zhang et al. 2025; Yifan et al. 2025) and to interpret human behavior while allowing machine-human collaboration (Huang 2025; Junfei & Yang 2025; Natarajan et al. 2023).

Embodied AI demands combining different technological systems and adapting it to the implementation context that sets a learning context. Different from AI that supports decision-making only while leaving execution unchanged, embodied AI is integrated in operational activities and so moves from a supporting to a constitutive element of value creation about how activities are performed, how they are linked, and who controls them. As such it changes business models of the firms that offer the systems. Most far-reaching changes occur for firms that implement embodied AI as a learning system composed of different technology that learns in its implementation context but also connects to external data. Embodied AI is associated with a learning loop inside the adopting firm, which connects with an external learning loop across the ecosystem of technology providers, component suppliers, software firms, platform orchestrators, and users. We conceptualize the two learning loops by the term double loop. The double loop influences transactions architectures of firm, but how? Accordingly, the purpose of our study is to examine dynamics of embodied AI on business models.

Our conceptual study puts forward that the double loop of embodied AI introduces a qualitatively different logic of value creation. Embodied AI systems implemented in firms, become integrated actors that exert some closed loop learning, but at the same time remain open to transfers of data with systems outside the firm. Data generated through use therefore travels beyond the adopting firm and feeds system updates, algorithmic refinement, component integration, and service innovation across the ecosystem. Embodied AI business models are consequently not firm-contained archi-

tectures, but interorganizational learning systems in which value creation depends on operational feedback, value delivery depends on continuous integration across providers and users, and value capture depends on who controls, accesses, and monetizes the learning generated in use. Hence, the integration of embodied AI brings strategic implications for how firms define value propositions, organize activities, coordinate with ecosystem partners, and capture value from their offerings.

The business model dynamics of embodied AI depend on the environment in which it is implemented. Our study focuses on agriculture, where embedded AI has been strongly proliferating with substantial dynamics although it has been paid little attention (Bouncken & Cesinger 2026a; Fitz-Koch et al. 2018). In agriculture, machines can be equipped with AI and sensors to autonomously or semi-autonomously carry out tasks, driving a substantial transformation of this traditional industry and its business models (Shamshiri 2024; Sharma et al. 2022; Wakchaure et al. 2023). Key players of agricultural operations and of the grand shift toward digitally enabled, knowledge-intensive farming systems are incumbent OEMs (e.g., John Deere, Claas, Agco), agritech startups, and research institutions (Fitz-Koch et al. 2018).

Our analysis carves out that business model dynamics occur on different levels and actors: new ventures, manufacturers, suppliers, service firms, and (industrial) users (Bouncken et al. 2021; Brousseau & Penard 2007). Value emerges during execution but remains contingent on the environment. Traditional product-centric logics centered on one-time equipment sales are increasingly complemented, and in some cases displaced by service-oriented and platform-mediated offerings. Machinery providers become increasingly dominant over other players by integrating hardware with proprietary software, analytics, and remote support, thereby developing hybrid product-service-platform business models rather than relying solely on transactional hardware sales (Finger 2023; Uyar et al. 2024). Technology firms deploy AI, cloud computing, and data analytics through subscription-based services and digital marketplaces, while agrochemical and agronomic firms combine field-level data with agribusiness expertise to offer algorithmic decision tools. As a result, value becomes performance-based, context-dependent, and continuously evolving, rather than predefined and stable. Mechanization remains important, but it is embedded in broader architectures of learning, coordination, and recurring value extraction.

Our study theoretically deduces a heuristic integrative business model framework. It combines typological business model elements, i.e., value creation, delivery, and capture with an activity-system perspective, extending prior frameworks to account for AI embedded in physical systems. We show that existing theories (Amit & Zott 2001; Zott & Amit 2010; Teece 2010) are limited in explaining value creation under conditions of continuous interaction, where activities are tightly coupled and value emerges through iterative feedback loops rather than discrete stages.

Overall, our study contributes to management research the first structured accounts of embodied AI and its business models dynamics. We show how business models shift from asset-based, episodic logics to adaptive, connected systems, and then explain how this transformation is generated through the reconfiguration of activity content, structure, and governance across ecosystems. Second, using agriculture as a revealing template, we provide a pioneering integrative account of embodied AI business models, demonstrating how value moves from product performance to con-

tinuous, data-driven workflows orchestrated across actors. Last, we conceptualize key tensions, openness vs. control, scaling vs. local fit, automation vs. reliability, and monetization vs. trust that shape business dynamics and determine emerging revenue logics in embodied AI ecosystems.

2 Theoretical background

2.1 Conceptual theorizing approach

As a conceptual theory-building article, our study develops a heuristic framework through conceptual synthesis, theory adaptation, and model building (Jaakkola 2020). We do not aim to provide a case-study analysis (Bouncken et al. 2026; Bouncken 2025) systematic literature review (Kraus et al. 2024), an empirical taxonomy, or a scoping review (Grønstad 2026). Instead, we use prior research as a theoretical resource for specifying how embodied AI alters business model dynamics. Conceptual papers contribute by integrating and extending existing theories to explain emerging phenomena that are insufficiently addressed by current conceptualizations (Gilson & Goldberg 2015; Jaakkola 2020).

Existing AI business model research explains value creation, delivery, and capture with its activity-system research explaining how activities are configured through content, structure, and governance (Jorzik et al. 2024), yet these perspectives largely assume that intelligence remains separate from physical execution or that value creation can be specified ex ante. Previous perspectives insufficiently capture business models in which AI is physically enacted, continuously updated through use, and dependent on loop interactions between machines, data, users, and environments. We therefore adopt a phenomenon-driven conceptualization strategy in which theoretical perspectives are selected according to their explanatory value for understanding the focal phenomenon (Jaakkola 2020).

Following Jaakkola (2020), we distinguish between domain theory and method theory. Initially, we selected literature around four bodies of work (domain theory) for developing the framework: embodied AI and robotics, AI-enabled business model innovation, digital business models, and agricultural digitalization. These bodies of work were not treated as parallel literature streams, but as contrasting theoretical lenses. Embodied AI research allowed us to identify the technological mechanisms that distinguish embodied AI from adjacent digital technologies, especially closed-loop adaptation, cognition-actuation coupling, and reliability-sensitive human–machine coordination The method theory is provided by the business model views on value creation, value delivery, and value capture (Teece 2010) and the activity-system dimensions of content, structure, and governance (Zott & Amit 2008; 2010) as an analytical lens. Combining these perspectives extends existing business model theory to contexts characterized by continuous interaction between intelligent physical systems, users, and ecosystems.

The framework emerged through iterative theory synthesis and adaptation. We identified the core mechanisms of embodied AI, examined their implications for

value creation, delivery, and capture (Teece 2010), translated these effects into activity content, structure, and governance (Zott & Amit 2008; 2010).

Agriculture research offered a revealing template than an empirical setting. Conceptual theorizing uses illustrative contexts to surface theoretical mechanisms (Jaakkola 2020). Environmental variability, asset intensity, and dependence on situated user expertise in agriculture make embodied AI business model dynamics especially visible. Then we formulate theoretically grounded claims about how specific embodied AI mechanisms generate business model dynamics. Consistent with conceptual theorizing (Gilson & Goldberg 2015; Hirschheim 2008; Jaakkola 2020), the propositions are grounded in logical argumentation rather than primary data.

2.2 Embodied AI

Embodied AI denotes a qualitatively distinct form of AI in which physical embeddedness is constitutive of how systems perceive, decide, and adapt (Chalmers et al. 2026; Bouncken & Cesinger 2026b; Haupt et al. 2025). Embodied AI characterizes intelligent machinery, typically robots, whose cognitive and decision-making capabilities emerge from physical interaction with the environment enabled by sensors, actuators, and adaptive control mechanisms (Huang 2025). It is enacted through real-world engagement by coupling perception with movement and control, so cognition is shaped by situated interaction and previous learning rather than abstract data processing alone (Yifan et al. 2025). Embodied AI systems integrate heterogeneous sensor inputs and multimodal perception, leverage self-supervised learning, and adaptive decision-making to enable context-sensitive behavior and safe coordination with humans in real-world environments (Junfei & Yang 2025; Yifan et al. 2025; Zhang et al. 2025). While AI generally demands stronger inter-firm collaboration and integration in platforms and ecosystems (Bouncken & Vogt 2026), embodied AI puts contextualized internal and external learning to the core.

Unlike embedded AI, which integrates algorithmic capabilities into devices to support predefined functions, embodied AI includes closed-loop processes where intelligence is enacted, continuously updated in use, and shaped by real-world conditions (Table 1). Through continuous feedback, embodied AI systems iteratively refine their behavior, develop context-dependent competence, and adapt to changing conditions, with human–robot coordination emerging as a key manifestation of this feedback through shared situational understanding and the dynamic allocation of tasks, roles, and resources (Yifan et al. 2025; Natarajan et al. 2023).

In addition, loop learning is no longer confined to the focal firm but becomes connected with a second (open) learning loop: The implementing firm learns from the system's use in its own operations, for example through improved routines, better process knowledge, more precise decision-making, and adaptation to local conditions. At the same time, the embodied AI system exchanges data with external providers of hardware, software, analytics, cloud infrastructure, and platform services. Learning therefore becomes distributed across organizational boundaries.

We define that embodied AI creates a double loop: an internal closed learning loop inside the adopting firm and an external learning loop across the ecosystem of technology providers, component suppliers, software firms, platform orchestrators, and

Table 1 Embodied AI: conceptual distinction

Concept	Core logic	Key limitation compared to embodied AI	How embodied AI differs
Embedded AI	AI integrated into devices	Typically supports predefined functions; limited continuous learning from real-world interaction	Learns and adapts continuously through real-world interaction
Cyber-physical systems	Integration of computation and physical processes	Focus on system integration and control, not adaptive learning through interaction	Double loops: Adds adaptive, learning-based intelligence in closed loops with connection to a second external loop
IoT-enabled machinery	Connectivity and data exchange	Emphasizes connectivity and monitoring; lacks autonomous decision-making and adaptive actuation	Enables autonomous decision-making and actuation
Decision-support AI	AI informs human decisions	Intelligence remains separate from execution; action is not autonomously enacted or learned from	Directly executes actions and learns from outcomes
Embodied AI	Double loop of closed-loop sensing-decision-action-learning and open loop with connection to externals Tight coupling with (prior) human workflows and decision-making, thus entails safety, liability, and human–machine coordination AI acts in the physical world, does not just analyze, thus its physical execution introduces risk and accountability Learning vs. dependency		

users. The double loop has internal effects as the implementing firm becomes more adaptive because embodied AI transforms operational experience into data, feedback, and learning. Its routines are no longer only human-experiential, but increasingly machine-mediated and data-enhanced. The double loop of embodied AI has an external effect, too: The implementing firm becomes more open and dependent because hardware and software providers can access, process, update, and monetize the data generated through the firm's operations. The user firm becomes part of the provider's learning infrastructure.

2.3 Embodied AI in agriculture

Embodied AI is strongly proliferating in agriculture (Bouncken & Cesinger 2026a, 2026b). Agriculture is changing by the replacement of manual labor with tractors and harvesters toward increasingly sophisticated forms of precision and smart farming driven by advances in digital technologies (Finger 2023; Wolfert et al. 2017). Telematics hardware (GPS, sensors, connectivity), Big Data, cloud computing, and AI as the core of smart farming enable real-time data collection (soil, weather, crop

conditions), remote diagnostics, usage tracking, predictive maintenance, data analytics, and automated operations (Javaid et al. 2022; Padhiary et al. 2025; Raj & Prahadeeswaran 2025; Spagnuolo et al. 2025).

Embodied AI allows agricultural machines to learn from data and improve processes reflective of the specific environment. Operations include land preparation and irrigation scheduling to seeding, spraying, and crop monitoring (Spanaki et al. 2021). By analyzing historical and field-level data, AI enhances core farming activities (Ahmed & Shakoor 2025). Decision and prediction models integrate historical and real-time field data, for instance, forecasting nitrogen needs by combining prior fertilization records with current canopy and soil measurements (Padhiary et al. 2024). Computer vision embedded into existing machinery or in robotic systems allows farmers to digitally detect weeds, diagnose diseases, and assess crop maturity (Assimakopoulos et al. 2024; Storm et al. 2024; Zhu et al. 2024).

As these systems rely on extensive and high-quality training data, datafication serves as a core resource for embodied AI. Embedded sensors, connectivity, cloud analytics, and robotics allow for automation not only of individual tasks (planting, spraying, harvesting) but of entire farm-management processes (Finger 2023; Javaid et al. 2022; Spagnuolo et al. 2025). For example, embodied AI supports automated operations, such as selective autonomous spraying, and augmentation, where farmers use AI-generated insights to refine management decisions. It depends on integrated perception–action-learning systems that adapt in situ to environmental variability (Casini et al. 2026). Embodied AI extends the capability of agricultural robots beyond simple automation to closed-loop interaction with the physical world, whereby systems continuously perceive, decide, act, and learn from feedback, often in real time (e.g., multimodal perception and task adaptation frameworks).

A combination of actors, including incumbent OEMs, agritech startups, as well as government-supported research programs trigger the transformation from mechanization toward digitally enabled, knowledge-intensive and embodied AI farming systems, where data and connectivity play a central role in enhancing productivity, sustainability, and operational efficiency.

Embodied AI in agriculture, particularly when it adapts to unstructured environments and uncertainty, opens opportunities for offerings that go beyond traditional product sales. Embedding AI in physical processes creates new strategic options for business model design: firms can bundle real-world autonomy with digital services (e.g., adaptive spraying, autonomous harvesting trajectories) and shift toward platform-mediated, outcome-driven value propositions. Concurrently, large technology firms and multinational agribusinesses are building digital platforms that integrate a wide array of agribusiness services within a shared data and service infrastructure.

2.4 Business model view

Technological innovation alone without an effective business model is insufficient for firm success (Teece 2010). A huge body of research has scrutinized what a business model is (Chesbrough & Rosenbloom 2002; Zott & Amit 2010), what builds its key components, and how business models are designed or innovated (Shamim et al. 2025). In general terms, a business model can be understood as the architecture

through which a firm creates value, delivers it to customers, and secures revenue in return. As (Teece 2010:172) puts it, the core of a business model lies in explaining how an organization provides value to customers, motivates them to pay for that value, and transforms those payments into profit.

A business model to deliver and capture value must exhibit a design of internal consistency (Teece 2018): its elements need to be aligned and the firm's capabilities must be able to support the value it promises to customers (Laudien & Pesch 2019). Alignment is also required between the business model and the company's organizational structure and managerial system (Zott & Amit 2008). The need for alignment helps explain why radical business model shifts, such as adopting unfamiliar technologies, serving entirely new customer groups, or redesigning core organizational processes, are difficult to achieve without substantial resources and strong managerial commitment.

The activity system view of business models (Zott & Amit 2008, 2010) proposes that firms orchestrate the content, structure, and governance of a set of activities to create value through the exploitation of business opportunities. According to this view, business model design is not about not just what the firm sells, but how the firm's activities are configured and connected across the focal firm, partners, and sometimes customers and as such what activities are performed, how they link, and who performs/controls them. Zott and Amit (2008) emphasize a set of business model design themes that explain value creation and innovation: novelty (new activities or linking activities in new ways), efficiency (reducing transaction/coordination costs), complementarities (bundling activities so "1 + 1 > 2"), and lock-in (retaining participants via switching costs, network effects, or loyalty mechanisms).

Business models gain importance in the context of environmental dynamics (Bouncken & Kraus 2025; Bouncken & Ratzmann 2026) but rarely work perfectly at the outset (Teece 2018). They typically require design refinement and sometimes complete redesign before they become sustainable sources of profit. Ventures are generally better positioned to make such changes than incumbent firms because they have fewer entrenched routines and assets that must be reconfigured (Holzmann et al. 2020). New technologies and new market conditions institutionalize change, which allow business models while also risking obsolescence when not experimenting with business model change (Clauss et al. 2020).

Especially digital technologies have provided innovation and change opportunities for businesses models (Bouncken et al. 2021). Just recently, AI has been considered as a trigger of business model innovation (Jorzik et al. 2024). Prior literature reviews show that AI enables new products and personalized services and thus reshapes business models by introducing new forms of value creation (Jorzik et al. 2024). While some studies focus on AI's impact on specific business model dimensions, others adopt a broader lens, examining transformations across firms, ecosystems, and entire industries (Jorzik et al. 2024). Overall, AI-driven business model innovation spans a continuum from incremental, adaptive changes to more radical, strategically driven reconfigurations (Jorzik et al. 2024). AI can act as an innovator by enabling new value propositions or extending existing models (Mostaghel et al. 2022), and as a disrupter when it redefines industry structures and competitive dynamics (Von Garrel & Jahn 2023).

Previous research has also proposed multiple frameworks and patterns for AI-based business models—ranging from data-driven and digitalized maintenance models to IoT and integration, servitization, and expertization approaches, highlighting their diversity and complexity (Bahoo et al. 2023). Moreover, AI is increasingly seen as reshaping traditional value creation processes and requiring alignment with broader ecosystem innovation (Burström et al. 2021).

Consequently, future research must place emphasis on how AI capabilities, stakeholder roles, and mechanisms such as automation, augmentation, and AI-supported decision-making drive business model dynamics (Jobstreibizer et al. 2025).

3 Conceptual framework

3.1 From embodied AI mechanisms to business model consequences

Embodied AI is characterized by four interrelated mechanisms that serve particularly relevant for dynamics. First, closed-loop adaptation in variable physical environments enables systems to continuously sense, act, and learn from feedback, allowing autonomous agents to respond effectively to changes in terrain, weather, or crop conditions (Zhang et al. 2025). Second, the coupling of cognition and actuation under uncertainty allows AI systems to integrate decision-making with physical execution, balancing risk and opportunity in complex, unstructured environments (Liu et al. 2025). Third, the value derived from embodied AI depends critically on its real-world reliability, operational safety, and effective coordination with human operators. Its benefits can only be fully realized if the system operates robustly and integrates seamlessly with human activities, especially in contexts where precision and safety are essential (Long, Zhao, Zhang, Zhang, Wang, Liu et al. 2025). Compared to disembodied or only embedded approaches, embodied AI closes the loop between perception and action, enabling real-time learning and environmental responsiveness that can substantially expand the operational capabilities of autonomous systems in dynamic settings. Fourth, the double loop of embodied AI changes transactions, allows closed loop learning while connecting learning and transactions to external partners, and inducing dependency. Insofar, embodied AI is not only a technical innovation but an enabler for data-driven business models, where operational performance, reliability, learning, and human interaction directly influence value creation and capture.

Unlike conventional digital or AI-driven business models, which typically enhance existing offerings through discrete digital features or analytics, embodied AI introduces a different logic. Rather than augmenting predefined activities, embodied AI embeds intelligence directly into physical operations through loop interactions of sensing, decision-making, and action.

Business model implications of embodied AI arise because its technical mechanisms alter the locus, temporality, and governance of value. Double loop adaptation changes the temporality of value creation. Value no longer resides primarily in the machine at the moment of sale, but evolves through repeated cycles of sensing, acting, feedback, and learning. As a result, the business model moves from product performance toward continuous workflow optimization, where value depends

on accumulated data, adaptive software updates, and repeated use in heterogeneous environments.

Cognition-actuation coupling changes the locus of value delivery. The business model consequence is therefore not merely more analytics or connectivity, but a shift toward operational performance promises, uptime management, autonomous or semi-autonomous service bundles, and outcome-oriented offerings. Because the system acts in the physical world, delivery becomes inseparable from reliability, safety, and situated human–machine coordination.

Reliability and safety change value capture. Since embodied AI executes actions under real-world uncertainty, failures may generate material damage, operational downtime, or safety risks. These conditions require service infrastructures, monitoring routines, liability arrangements, data governance, and trust-building mechanisms. Consequently, recurring, usage-based, and performance-linked revenue models can only scale when customers perceive the system as reliable, accountable, and fairly governed. The business model distinction from IoT, digital servitization, and disembodied AI is therefore not the presence of data or connectivity alone, but the coupling of learning, execution, accountability, and monetization in physical operations.

3.2 From assets to adaptive systems

Embodied AI fundamentally shifts business models from asset-based, episodic transactions toward adaptive, data-driven systems in which value emerges through continuous interaction across interconnected actors and infrastructures. Embodied AI business captures an overarching shift in how value is organized across machinery, input use, service provision, data infrastructures, and coordination mechanisms among multiple actors, including OEMs, platform providers, dealers, and users.

Agriculture illustrates these dynamics: In pre-digital business models of agribusiness, equipment largely functions as a standalone asset that farmers own and operate, with performance primarily defined by mechanical capability and the farmer's experiential expertise. Value creation is tightly coupled with standardized routines. In agriculture it relates to the uniform application of seed, fertilizer, and crop protection products, and to the ability to manage variability through human judgment. Value delivery is episodic: OEMs and service partners are most visible at the moment of purchase and when something breaks, while maintenance and support are largely reactive and localized. Value capture follows the same rhythm. Revenue concentrates on one-time hardware transactions and is reinforced by spare parts and maintenance service that depend on the depreciation and replacement cycle of machinery.

Embodied AI transform value capture by enabling scalable and resilient revenue architectures. Instead of being anchored mainly in equipment sales and replacement cycles, income increasingly comes from subscriptions for telemetry and automation, data analytics and software licenses, digital upgrades, and service contracts that may be tied to uptime or outcomes. Because value now depends on the alignment of hardware, software, services, and on accumulated data histories and on routines, switching costs tend to rise, strengthening lock-in and allowing firms to appropriate value continuously rather than primarily at the point of sale.

Table 2 captures the transition organized around ownership of standalone assets and standardized routines to agribusiness organized around connected infrastructures, continuous optimization, and ecosystem coordination. In that sense, embodied AI is not merely a technological upgrade; it represents a business model dynamics driver, in which data and software become central to how value is created, delivered, and captured. Table 2 also reflects how these models broaden adoption pathways: subscription tiers, pay-as-you-use models, automation, and retrofit kits reduce the initial cost of entry and allow smaller or resource-constrained farms to access capabilities that previously required large capital investments.

In the activity-system view, a business model is defined by the content of activities (what is done), their structure (how activities are linked and sequenced), and their governance (who performs and controls them) (Amit & Zott 2001; Zott & Amit 2010). Embodied AI with its different components (diverse machinery components, software, data, and learning systems) shifts the analysis from "what a firm sells" to how value is organized as an interdependent system of activities. In agribusiness, dynamics of embodied AI integration are not confined to any single actor (e.g., OEMs) but unfold in the entire agribusiness ecosystem through reconfigurations that span machinery, data infrastructures, software services, dealer/service networks, complementors, and farmers. Through repeated sensing-decision-action cycles, embodied AI continuously converts operational experience into learning and workflow improvements. Consequently, value shifts from the static performance of physical assets toward the continuous optimization of operations, making adaptive, data-driven workflows a key source of competitive advantage.

Table 2 Pre-digital versus AI driven business models

Conventional business model	Embodied AI business model
Equipment as standalone assets	Machinery as nodes in digital ecosystems/management platforms; In agriculture integration across farm data, weather, supply-chain; traceability
Selling machinery and its devices once; income from volume, parts, and maintenance such as tractors/harvesters	Selling hardware plus subscription/telemetry services plus data analytics plus software licenses plus automation kits
Uniform application of input factors. In agriculture: seeds, fertilizer, herbicides, pesticides etc	Sensors, data, AI enabled optimization/data-driven applications e.g., precision farming:
Reactive maintenance and ad-hoc servicing	Predictive maintenance, real-time diagnostics, remote software/firmware updates, monitoring-
Equipment depreciation and replacement cycles drive revenue	Recurring revenue from software, services, upgrades, data and analytics, and predictive maintenance
Industrial users own and operate machinery; OEMs supply spare parts and mechanical support	OEMs (or platform providers) provide autonomous/assisted machinery plus remote management, data services, and/or outcomes-based contracts

Proposition 1 *Because embodied AI couples sensing, decision-making, and physical action in closed-loop systems, firms are more likely to shift value creation from asset-based product performance toward adaptive, data-driven workflow optimization, especially in environments characterized by high operational variability.*

Reinterpreting the "old vs. new" contrast in Table 2 through the activity system business model lens clarifies what is structurally changing. Pre-digital agribusiness is characterized by an activity system in which the content concentrates on manufacturing and selling equipment, complemented by episodic parts-and-service activities. Structure is comparatively linear and punctuated. Governance largely resides with farmers' ownership and operation, with OEMs and dealers intervening primarily at transactional moments. Differently, for embodied AI models, the activity content expands to sensing and telemetry, data aggregation, analytics and decision support, remote diagnostics and updates, automation feature provisioning, and in some cases outcome management. Activity structure becomes continuous and networked, because equipment is repositioned as a node in a broader platform-mediated system that links field operations with agronomic models, weather data, traceability requirements, and complementary applications. Governance becomes strategically salient and contested, because value increasingly depends on control over interfaces, data access and portability, complementor participation rules, and monetization rights, which are critical in ecosystems (Krome et al. 2025).

The activity-based model also explains why particular business models create and appropriate value. The design themes of novelty, efficiency, complementarities, and customer lock-in map directly onto mechanisms associated with platformization and recurring revenue logics (Zott & Amit 2010). Embodied AI based activity systems (as already integrated within smart-farming) generate efficiency through precision application and predictive maintenance, complementarities through hardware–software–service bundling and cross-partner integration, and novelty through newly feasible activities (e.g., per-acre feature licensing, remote optimization, retrofit-to-subscription pathways). At the same time, many configurations intensify customer lock-in via accumulated data histories, workflow embedding, switching costs, and network effects, rendering governance choices central to value distribution and power asymmetries. Unlike analytical AI, which supports decision-making while leaving execution unchanged, embodied AI directly participates in operational activities through sensing, decision-making, and actuation. As intelligence moves from a supporting role to a constitutive element of value creation, firms must redesign what activities are performed, how they are linked, and who controls them. This transforms the underlying architecture of the business model rather than simply augmenting existing processes.

Proposition 2 *Because embodied AI embeds intelligence directly in physical execution rather than in analytics alone, value creation increasingly depends on the reconfiguration of sensing, decision-making, service, and coordination activities, rather than on the augmentation of existing processes alone.*

4 Integrative business model grid for embodied AI

The previously outlined shift from asset-based to adaptive system-based business models does not explicitly account for the roles of different actors in the supply chain and the evolving linkages among them. Agriculture serves as an illustrative template of these dynamics, where incumbent OEMs, often referred to as agritechs, occupy a central position that affords them both significant responsibility and unique opportunities in navigating an industry undergoing profound technological and organizational transformation (Fitz-Koch et al. 2018).

To analytically capture these actor constellations and evolving linkages, we develop an integrative grid that combines Teece's business model perspective with the activity-system view. The grid focuses on how the shift from asset-based to adaptive system-based business models is enacted through the reconfiguration of activities and their interdependencies across multiple actors. Within Teece's (2010) framework, shifts manifest as changes in value creation, delivery, and capture. However, this perspective remains largely outcome-oriented and does not explicate how these changes are generated. The activity-system perspective (Zott & Amit 2008, 2010) complements this view by conceptualizing business models as configurations of activities defined by their content, structure, and governance, thereby allowing us to trace how dynamics unfold within and across firms.

In the model of Teece (2010), the transformation of business models at the level of incumbent OEMs implies that they are reconfiguring value creation, delivery, and capture. The activity-system perspective (Zott & Amit 2008, 2010) complements this view by conceptualizing business models as configurations of activities defined by their content, structure, and governance, thereby allowing us to trace how dynamics unfold within and across firms. Embodied AI is particularly consequential in this regard because it redefines what activities are performed, how they are linked through continuous feedback and coordination, and who controls critical resources and interfaces. As a result, business model dynamics emerge not only from changes within firms, but from the reorganization of interdependent activities across OEMs, platform providers, service actors, and users.

Our grid (Table 3) maps horizontally the value dimensions and vertically the elements of the activity system. Each row asks: What changes in the activities and linkages produce this outcome? Second, it separates activity content from activity structure to show that dynamics are not only about "adding digital features" but about reorganizing sequences, feedback loops, and governance across ecosystem actors.

The integrative grid should therefore be read as a mechanism-based framework rather than as a descriptive classification. Each cell links a distinctive property of embodied AI to a specific business model consequence. Closed-loop adaptation explains why value creation becomes iterative and workflow-based. Cognition-actuation coupling explains why value delivery becomes tied to execution, uptime, intervention capacity, and operational performance. Reliability, safety, and human–machine coordination explain why value capture requires trust, accountability, liability arrangements, and governance of data and interfaces.

The activity-system perspective adds understanding to how embodied AI changes what firms offer, what activities must be performed, how these activities are con-

Table 3 Integrative embodied AI business model grid

	Activity content (what activities)	Activity structure (how linked/sequenced/governed)	Activity governance (who performs the activity and where)
Value creation	Expansion from machinery production to continuous sensing, data capture, analytics, and adaptive control *Closed-loop adaptation:* ongoing transformation of data into recommendations and actions	Shift from one-time machinery event and product performance to iterative, feedback-driven workflows across fields and seasons *Closed-loop mechanism:* data to insight to actuation to learning continuously refine outcomes	Shared control over data and learning processes across partners in digital platforms and data ecosystems *Mechanism*: distributed innovation and model improvement through ecosystem data flows
Value delivery	From episodic to continuous service operations (predictive maintenance, updates, training, in-season optimization) *Reliability and coordination*: ensuring safe, robust operation in real environments	Shift from episodic touchpoints to continuous lifecycle pipelines embedded in real-time execution *Cognition–actuation coupling:* deploy to monitor to optimize to update; delivery occurs through ongoing interaction between AI decisions and physical execution	Orchestration of digital platforms and data ecosystems across OEMs, dealers, platforms, and complementors *Mechanisms*: governance to ensure interoperability, uptime, and exception handling under uncertainty
Value capture	Monetization from one-time sale and episodic maintenance / repair to subscriptions usage-based, and outcome-based models tied to AI-driven performance and learning *Closed-loop adaptation*: value scales with accumulated data and system improvement	Monetization embedded in usage and performance cycles (seasonal, per hectare, per hour) *Mechanism*: continuous feedback stabilizes recurring, performance-linked income streams	Distributed governance of digital ecosystems via contracts, data ownership, IP rights, and liability frameworks *Reliability and trust*: safety, accountability, and switching costs for sustained value capture

nected, and who controls them. Activity content expands toward sensing, data capture, analytics, remote intervention, predictive maintenance, adaptive control, safety validation, and user training. Activity structure shifts from episodic transactions to continuous deploy-sense-decide-act-learn cycles. Activity governance becomes more distributed and contested because OEMs, dealers, platform providers, complementors, and users all contribute to the functioning of the embodied AI system. These changes explain why embodied AI business models differ from conventional digital servitization: value depends not only on service augmentation around a product, but on the orchestration of a continuously learning physical-digital operating system.

Value creation: (row 1) of embodied AI shifts the object of exchange from a primarily mechanical asset to an integrated physical–digital system where performance is evaluated in farm outcomes rather than mechanical specifications alone. Embedding sensors, connectivity, automation, and AI are not merely featuring accretion but an architectural move from isolated implements of digital elements toward connected and interoperable systems.

This closed-loop logic expands activity content beyond machinery production to include sensing, data capture, agronomic analytics, automation, and interface design. Software bundles intensify the shift because they continuously transform operational data into recommendations and adaptive control, turning value creation into an ongoing, lifecycle-based process rather than a one-time attribute at purchase.

Structurally, this transforms value creation from a static one-time performance logic (machine capability at purchase) to an iterative workflow logic, where feedback loops across field operations and seasons become iterative loops. Ecosystem partners drive continuous improvement. Consequently, value creation and competitive advantage move beyond the OEM's capacity to design and manufacture "better iron" alone toward the ability to deliver repeatable and reliable data-informed workflows across heterogeneous farm contexts resulting in improvements in efficiency, timeliness, sustainability, and transparency.

Value delivery: (row 2) fundamentally evolves in the context of embodied AI due to its closed-loop logic from a traditional "sell-and-service" cycle to continuous, lifecycle-based service provision, where the OEM's role extends far beyond machine delivery and centers on operationalizing integrated functional bundles. Because value emerges from ongoing feedback loops between machines, data, and environment, delivery becomes inseparable from execution: performance depends on continuous data flows, software updates, and adaptive interventions. Accordingly, OEMs deliver not standalone equipment but integrated socio-technical systems that connect machinery with software platforms, dealers, service infrastructures, and other on-farm technologies.

Activity content expands from reactive repair toward proactive uptime management including remote diagnostics, predictive maintenance, firmware updates, onboarding and training, in-season optimization, and uptime management. As a result, the dealer network and digital service layer become not peripheral complements but core delivery channels through which the OEM stabilizes adoption, embeds digital services into farmers' routine practice, and ensures customer lock-in while reducing complexity for farmers.

It shifts value delivery structurally into a continuous lifecycle pipeline requiring orchestration across OEMs, dealers, platforms, and complementors, including exception handling when connectivity or interoperability fails. Interoperability becomes critical, as closed-loop learning depends on seamless integration across equipment, data environments, and ecosystem actors. New service architectures reinforce the dynamics. Value delivery occurs through subscription-based software, pay-per-use automation, and retrofit kits lower initial adoption barriers and allow farms with limited capital to access functionality that would otherwise require major equipment replacement or premium configurations.

Embodied AI then repositions OEMs from equipment providers to providers of operational performance, with dealer networks and digital service layers becoming core delivery channels that embed services into daily practice and foster relational, service-rich engagement. Ultimately, the closed-loop nature of embodied AI makes value delivery contingent on a lifecycle pipeline and continuous system orchestration, learning, and human–machine coordination, where reliability, safety, and trust become central to scalable adoption and monetization.

Value capture (row 3): shifts fundamentally with embodied AI, driven by its closed-loop logic of sensing, learning, and acting. Unlike traditional episodic hardware sales, embodied AI continuously updates and adapts through data-driven feedback from its environment, decoupling revenues from one-off equipment transactions and enabling lifecycle-oriented business models. Revenue increasingly derives from recurring service and software fees, usage-based pricing, and outcome- or performance-linked contracts that are tied directly to insights generated by the AI, automation, and remote monitoring. The closed-loop system ensures that operational performance continuously informs AI improvements, which in turn enhance farm outcomes, creating stable, repeatable revenue streams rather than cyclical, transaction-heavy hardware sales. Scalability improves as these software- and data-driven services carry lower marginal costs and remain embedded in the farmer's workflow, with safety, accountability, and trust as critical enablers for adoption and monetization.

Activity content shifts from replacement cycles towards recurring monetization mechanisms and revenue streams: subscription tiers, per-acre licensing, data services, predictive maintenance contracts, retrofit kits, and outcome-based agreements. Structurally, due to the enabled by the closed-loop logic of embodied AI. monetization must be embedded in usage cycles (seasonal, per hectare, or per hour). Activity content thus expands beyond selling an intelligent machine to operating a deployed, continuously learning system that integrates multi-sensor data capture and fusion, safety validation and risk monitoring, on-site integration, teleoperation/exception handling, continuous model updates, and user training for human–robot coordination. In this system, the components of embodied AI, deployment, sensing, decision-making, actuation, and learning, form an iterative operating architecture, in which each loop feeds back into the next, continuously refining performance, supporting monetization, and reinforcing value capture over time.

A defining feature of embodied AI is that performance improves through repeated interaction with dynamic environments. Continuous sensing-action-feedback cycles generate an expanding knowledge base that enables ongoing adaptation and optimi-

zation, shifting value creation from one-time machine performance toward the cumulative improvement of workflows and outcomes.

Proposition 3 *As embodied AI continuously learns through repeated sensing-action-feedback cycles, value creation increasingly shifts from one-time machine performance toward the continuous improvement of operational workflows.*

Data from diverse sources and the integration of multiple technology elements, machinery, sensors, software, create interdependent ecosystems that require both collaboration and governance among actors. Hardware–software-service ecosystems must allow seamless coordination across these elements. However, switching costs for farmers rise, enabling OEMs to capture value not just at purchase but through ongoing engagement across the equipment's operational life. Governance is increasingly distributed, with critical activities handled by complementary partners (robotics OEMs, software/platform providers, integrators, service teams), and control exercised via contracts, trust, interfaces, data access, IP rights, and liability frameworks. Embodied AI business models' shift thus is simultaneously technological (new digital activities), organizational (new sequences and service operations), and ecosystemic (new governance and orchestration requirements). It is about data rights, complementor participation, and reliability in real-world farm contexts, not solely on superior hardware. Taken together, the distinctive characteristics of embodied AI reshape the mechanisms through which firms create, deliver, and capture value by changing the underlying activity systems.

Proposition 4 *Because embodied AI links value delivery to reliability, safety, and human–machine coordination in physical operations, firms are more likely to adopt recurring, usage-based, or performance-linked revenue models.*

5 Discussion

This study develops a novel theoretical perspective that positions embodied AI as a distinct and underexplored source of business model dynamics, arising from intelligence embedded in physical operations. Existing research has predominantly conceptualized AI as a disembodied capability that enhances analytics, automation, or decision-making, while largely overlooking forms of AI embedded in physical operations (Kanbach et al. 2024; Huang 2025; Jorzik et al. 2024; Junfei & Yang 2025). Our framework advances this conversation by showing that embodied AI is qualitatively different: intelligence is embedded in physical operations and unfolds through a double loop: the closed-loop coupling of sensing, decision-making, and action and the outside loop of connecting learning and data to external providers of technology. As a result, business model dynamics are not driven merely by better information processing or component based "add-in intelligence" to machines, but by systems that continuously act, learn, and adapt in real environments, and connect to the outside.

The present study advances one of the first theoretical accounts of embodied AI in management research, explicitly connecting it to business model dynamics and

extending the analysis systematically to agriculture. We do not claim that embodied AI automatically produces one universal business model. Rather, we theorize a mechanism-based transition logic. Embodied AI generates business model dynamics when double loops, closed-loop adaptation, cognition-actuation coupling, and reliability-sensitive human–machine coordination reconfigure activity content, activity structure, and activity governance. The resulting business model outcomes depend on contextual conditions. Our contribution lies in specifying the generative logic through which embodied AI reshapes business models, rather than in offering a deterministic or exhaustive typology.

Still, we offer an illustrative context of agriculture that offers an empirically rich, but also traditional industry undergoing significant transformations, making it a useful template for studying AI-driven dynamics in business model d. This context allows us to ground and explicate our integrative framework on embodied AI and activity systems, demonstrating the shift from traditional asset-based models to double loop-based business models.

5.1 Theoretical implications

First, our transition map (Table 2) highlights a fundamental structural shift from asset-based transaction-oriented business models toward connected, ecosystem-based infrastructures, in which value from embodied AI emerges through continuous optimization and recurring monetization. It is based on the specification of embodied AI as given in Table 1. The business model dynamics initiated by embodied AI are not incremental. They redefine the unit of analysis from the discrete machine to the workflow, and from single-firm offerings to interdependent socio-technical systems where performance depends on data flows, interoperability, and service operations across multiple actors. Theoretically, our analysis on embodied AI dynamics refines and extends the technology implications perspective on AI-driven business model innovation (Jorzik et al. 2024).

While prior work conceptualizes AI as a largely peripheral enabler of incremental efficiency gains, our findings show that this interpretation no longer holds in the context of embodied AI. Due to its loop coupling of perception, decision-making, action, and external linkages, embodied AI shifts from supporting existing processes to executing core activities, thereby relocating the locus of value creation. From an activity-system perspective (Zott & Amit 2008, 2010), AI is no longer an add-on but becomes central for operations, continuously reconfiguring interdependent processes through feedback-driven learning cycles. Value increasingly stems from the ability to transform real-world variability into actionable intelligence and, in some cases, into autonomous execution. This value change not only expands the content of activities (e.g., sensing, analytics, automation) but fundamentally alters their structure, turning farming operations into learning-oriented workflows that evolve across contexts and over time.

Second, by integrating the value creation-delivery-capture logic in the model of Teece (2010) with the activity-system perspective (Zott & Amit 2008, 2010), we specify a generative mechanism through which embodied AI drives business model dynamics. Embodied AI transforms the nature of activities themselves, it expands

activity content (e.g., telemetry, analytics, automation, interoperability) while restructuring activities into iterative closed loops (deploy-sense-decide-act-learn) that connect development and use across contexts and over time. These loops make value delivery inseparable from execution and reposition firms as providers of continuous operational performance rather than discrete products.

In parallel, value capture shifts toward recurring and usage-based models, such as subscriptions, per-acre licensing, predictive maintenance, and outcome-based contracts. Thus, activities are no longer static or sequential but become loop based adaptive processes tightly coupling sensing, decision-making, and execution. Second, existing frameworks assume stable, predefined value propositions and a separation between design and execution. In contrast, embodied AI embeds value creation and delivery within continuous system orchestration, where performance emerges from the alignment of hardware, software, data pipelines, updating routines, and human–machine workflows across multiple actors. As a result, value is not delivered at a single point in time but unfolds through lifecycle-based processes, requiring ongoing coordination, remote support, and adaptive interventions. It challenges the traditional "sell-and-service" logic and extends theory toward a processual and execution-centered view of business models. Yet it also increases interdependencies between actors, technologies, and environments, thereby complicating governance and coordination. Moreover, the boundaries of the firm blur as value creation increasingly depends on real-time data flows, human–machine interaction, and ecosystem integration.

Third, embodied AI requires business models to be understood not as static configurations, but as relational, evolving architectures shaped by closed-loop system dynamics. The resulting tensions (see Table 4) mark another central theoretical contribution. These tensions are not incidental but endogenous to the closed-loop nature of embodied AI, where learning depends on openness while value capture requires control, scaling relies on standardization while performance demands localization, automation increases value but also risk, and monetization hinges on trust grounded in reliability and safety. This reframes core business model design themes such as efficiency, complementarities, and lock-in as outcomes of continuous interaction between hardware, software, data, and human actors, mediated by governance choices rather than isolated firm decisions. For business model theory, this implies two key extensions.

First, it shifts the analytical focus from asset-centered offerings to workflow-centered activity systems, where value is created and delivered through repeated cycles of sensing, learning, and service intervention. Second, it shows that business model design becomes inseparable from ecosystem governance, as value increasingly depends on interfaces, data flows, and coordination across organizational boundaries (Bouncken & Kraus 2022). Consequently, business models in embodied AI contexts must be theorized as co-evolving systems shaped by complementor participation, standardization dynamics, and institutional constraints, rather than as firm-contained configurations (Adner & Kapoor 2010; Vargo & Akaka 2012). Third, embodied AI business models must then be designed as carefully balanced configurations, where enabling mechanisms, risks, and governance solutions are jointly aligned. Core design choices are no longer discrete trade-offs, but a dynamic balancing shaped by closed-loop system dynamics, in which value creation, delivery, and capture depend

Table 4 Embodied AI tensions, enabler, risks, and solution

Tensions	Loop enabling mechanisms	Risks	Moderators	Impacts	Solutions
Openness (vs. control)	Double-loop requires broad data integration and interoperability across systems to improve learning and performance for heterogeneous workflows	Value leakage through commoditization Loss of strategic control over interface and data, and relationships	Balances proprietary capture vs. ecosystem participation	High control supports subscription contracts. High openness enables platform- or partner-driven revenue but endangers exclusivity	Selective openness: interoperability standards (ISOBUS-like) and governance of critical data layers
Scaling (vs. local fit)	Loop benefits from large-scale data but depends on context-specific learning in heterogeneous environments while calling for economies of replication (across seasons, operational scalability, standardized services)	Performance failures due to environmental variability. For example, soil, microclimate, crop system), fragmentation through excessive customization	Determines replicability and standardization	High scalability favors low-marginal-cost recurring or usage-based revenue High local adaptation increases service cost, limits predictability	Hybrid architectures: global models plus local adaptation, human-in-the-loop (dealers, agronomists); localized and cooperative datasets
Automation ambition (vs. reliability constraints)	Cognition–actuation coupling under uncertainty increases value potential (time savings, input reduction, yield stability) through autonomous execution Workflow simplification for users	High cost of failure. For example, crop damage, safety, downtime at critical farming windows Un-learning of routines. Reduced willingness to adopt models	Shapes achievable autonomy and performance guarantees	High automation enables outcome- or performance-linked contracts Reliability limits necessitate hybrid service models or upfront fees	Substantial testing and training in different contexts Variation and validation protocols, third-party certification, and monitoring
Monetization (vs. trust)	Predictable revenue via subscriptions. For example, usage-based billing, per-hectare licensing. Continuous improvement funded by recurring cash flows	Perceived unfairness, data-ownership conflicts, lack of transparency undermining adoption	Influences customer willingness to accept novel pricing	High trust allows risk-sharing and premium usage/outcome-based models Low trust favors upfront sales or simple service fees	Trust-based governance and clear data rights, right-to-repair, dispute resolution mechanisms

on continuously managing interdependencies between technology, ecosystem actors, and institutional conditions.

Fourth, embodied AI transforms technical capabilities into a fundamentally new management logic: its closed-loop integration of sensing, decision-making, and

action shifts firms from episodic, product-based value creation to continuous, feedback-driven operations, where value is dynamically generated and refined in use. Learning systems become organizational dynamic capabilities, requiring constant data integration, experimentation, and adaptation, while the tight coupling of software and physical execution elevates reliability, safety, and uptime to core managerial priorities. At the same time, data intensity turns information into a strategic asset, demanding robust governance across increasingly interdependent ecosystems, and human-AI interaction reshapes workflows, skills, and decision rights. As a result, management moves beyond optimizing isolated products toward orchestrating interconnected systems of actors, technologies, and data, where competitive advantage lies in coordinating continuous learning, scaling services, and capturing value from embedded, evolving use rather than one-time transactions.

5.2 Systemic tensions in embodied AI business models

Building on the integrative grid, embodied AI introduces systemic strategic tensions (see Table 4) that are endogenous to its closed-loop mechanisms, as these simultaneously enable and constrain business model design.

One tension concerns *openness versus control*. Openness supports interoperability and distributed innovation (of the soft- and hardware components), lowering adoption frictions for farmers who operate heterogeneous fleets and depend on cross-brand compatibility. Control supports lock-in and value capture by concentrating value appropriation in platform owners and by raising switching costs through proprietary data histories and embedded workflows. Embodied AI intensifies the tension between openness and control: continuous learning depends on broad data access and interoperability across heterogeneous systems, yet value capture relies on controlling data flows, interfaces, and accumulated learning. This tension thus requires selective openness, where firms support interoperability (e.g., standards such as ISOBUS-like architectures) while strategically governing critical data layers.

Proposition 5 *As embodied AI relies on distributed learning across heterogeneous data sources and ecosystem actors, value creation increasingly requires openness through interoperability and data sharing, whereas value capture increasingly requires control over interfaces, customer relationships, and accumulated learning, giving rise to an openness–control tension.*

A second tension concerns *scaling versus local fit*. AI-enabled offerings promise scale economies through software replication, but agribusiness contexts are highly variable. Robust performance often requires localized knowledge and continuous adaptation to regional contexts and changing climatic conditions, thereby limiting standardization. The closed-loop mechanism of embodied AI reinforces the tension between scaling and local fit, as learning effects benefit from large-scale data aggregation, while performance remains highly context-dependent, requiring local adaptation. Addressing this requires hybrid architectures that combine global models with local adaptation, supported by human-in-the-loop actors such as dealers and agronomists and by localized or cooperative datasets.

Proposition 6 *As embodied AI benefits from learning across large-scale datasets and operating contexts, value creation increasingly requires scalable architectures and standardized solutions, whereas reliable performance increasingly requires adaptation to heterogeneous local environments and use conditions, giving rise to a scaling-local fit tension.*

Third, embodied AI creates tensions of *automation ambition versus reliability constraints*. Cognition-actuation coupling under uncertainty amplifies the tension between automation ambition and reliability constraints: as AI moves from decision support to autonomous execution, value potential increases, but so do the risks of failure in uncertain, heterogeneous environments, making reliability a limiting condition for adoption and monetization. In agriculture, where operating environments vary widely across farms and seasons, the risk of technology not functioning when needed or in ways aligned with farmers' requirements can be substantial. Such reliability concerns may reduce users' (farmers') willingness to pay for outcome-based contracts and can slow down the diffusion of autonomous embodied AI-based solutions. This necessitates robust validation regimes, including extensive testing across contexts, staged deployment of autonomy, certification, and continuous monitoring.

Proposition 7 *As embodied AI increasingly couples cognition and physical action in autonomous operation, value creation increasingly depends on higher levels of automation and autonomous execution, whereas value delivery increasingly depends on reliability, safety, and predictable performance under uncertainty, giving rise to an automation-reliability tension.*

Finally, a fourth tension concerns *monetization versus trust*. The dependence on reliability, safety, and human–machine coordination sharpens this tension: while recurring, performance-based revenue models stabilize income, they also advance concerns about transparency, data rights, and fairness, making trust a prerequisite for scalable value capture. This indicates the strategic importance of governance mechanisms that signal trust and reliability, such as clear data rights, transparent pricing, right-to-repair provisions, and strong human support through dealer networks and dispute resolution structures.

Proposition 8 *As embodied AI shifts value capture toward recurring, usage-based, and outcome-linked revenue models, monetization increasingly depends on continuous customer participation and data-enabled service relationships, whereas adoption increasingly depends on trust in system reliability, transparency, data governance, and perceived fairness, giving rise to a monetization-trust tension.*

Key tensions in embodied AI moderate the feasibility and outcomes of different revenue logics. Table 4 summarizes how these embodied AI tensions shape the ability to capture value through recurring, usage-based, or outcome-linked models. The degree of openness in data, interfaces, and ecosystem participation shapes how value can be captured. High control reinforces proprietary revenue streams, such as subscription or outcome-based contracts, but may limit ecosystem-based ser-

vices and partner-driven monetization. Conversely, greater openness supports collaborative or platform-based revenue models, though it can reduce exclusivity. The tension between broad scalability and local adaptation influences the feasibility of standardized recurring or usage-based revenue models. High scalability enables replicable, low-marginal-cost revenue streams, while extensive local customization increases service costs, reduces standardization, and constrains predictable revenue. The level of automation achievable without compromising reliability affects which revenue logics are viable. High automation can support performance- or outcome-linked contracts by ensuring consistent results, whereas reliability constraints may require hybrid service models or restrict premium monetization tied to autonomous performance. Finally, the adoption of novel pricing models, such as outcome- or usage-based approaches, depends on customer trust. Strong trust enables high-value, risk-sharing contracts, while low trust limits monetization options to upfront payments or simpler service fees. The former discussion revealed a set of tensions that occur with the dynamics of embodied AI integration.

Proposition 9 *(System-Level Tensions): Because sensing, decision-making, actuation, learning, and ecosystem governance are interdependent in embodied AI systems, the tensions of openness-control, scaling-local fit, automation-reliability, and monetization-trust are more likely to emerge simultaneously and reinforce one another.*

5.3 Management implications of embodied AI for business model design

Embodied AI fundamentally reshapes managerial priorities by shifting agribusiness from product-centric competition to the orchestration of continuous, data-driven workflows. Dynamics together with managing embodied AI tensions has implications for key actor groups, influencing capabilities, roles, and revenue logic.: openness vs. control, scale vs. local fit, automation ambition vs. reliability, and monetization vs. trust.

OEMs are transforming from product manufacturers into orchestrators of integrated AI-driven workflows, requiring capabilities beyond engineering: spanning software integration, data governance, and service operations while balancing interoperability with control over critical data. Reliability, safety, and uptime have become core value drivers, demanding investments in deployment cycles, remote support, and dealer training that bridge machinery and software. Managers must navigate persistent tensions: automation ambition versus reliability, ensuring rigorous validation, testing, and risk management; scaling versus local fit, designing hybrid architectures that deliver global efficiency while adapting to local conditions; and monetization versus trust, creating pricing models, subscriptions, usage-based services, or outcome-linked contracts, that align value with transparency and credibility. Success hinges on orchestrating hardware, software, and human actors in continuous feedback loops, enabling AI adoption, ecosystem participation, and sustainable revenue while maintaining safety, reliability, and trust at scale.

Dealers are evolving into essential delivery partners in AI-driven agricultural ecosystems, providing onboarding, training, and real-time operational support. The dynamics require expanding digital and analytical capabilities alongside traditional

mechanical expertise, enabling interoperability without compromising service differentiation. At the same time, dealers must navigate key tensions: openness versus control, by facilitating cross-platform integration while preserving distinctive services; scaling versus local fit, by delivering context-sensitive guidance that aligns standardized AI outputs with local conditions; automation ambition versus reliability, by coordinating field-level monitoring, adaptive oversight, and rapid response to failures; and monetization versus trust, by ensuring transparent pricing, support, and fair data practices that reinforce adoption. Success depends on leveraging these capabilities to build trust, optimize deployment, and continuously feed insights back into AI systems, sustaining both operational performance and ecosystem value.

Agritech startups and new entrants must navigate complex ecosystem dynamics, balancing the need to complement incumbent platforms with the pursuit of specialized niches. Success hinges on enabling interoperability, delivering modular innovation, and addressing targeted problems such as analytics modules or autonomy tools, while managing dependence on dominant platforms and securing access to critical data. To scale sustainably, startups must align with evolving standards and governance structures, demonstrate reliable services, maintain transparent pricing, and ensure safe automation. Regarding the tension of monetization versus trust, credibility emerges as a central driver of adoption, requiring offerings that are both technically robust and perceived as fair and dependable within the ecosystem.

Finally, farmers gain from performance-driven AI solutions but face increasing dependence on integrated digital ecosystems, creating risks of lock-in and reduced operational control. They must navigate openness versus control by understanding data-sharing implications and ensuring transparency without compromising efficiency or privacy. Balancing scaling versus local fit requires integrating AI into site-specific routines with flexible operations and a learning mindset, avoiding over-reliance on rigid systems. Across automation ambition versus reliability, farmers weigh efficiency gains against potential system failures, relying on governance mechanisms and clear escalation protocols to maintain confidence and ensure safe adoption.

6 Limitations and future research agenda

The first limitation is our conceptual methodology. The conceptual framework imposes a coherent structure on a fast-moving and heterogeneous domain, which inevitably simplifies business models in agricultural practice: business models vary by crop system, farm size, and regional infrastructure and context. A second limitation concerns our focus on dynamics of a specific industry, agribusiness (Javaid et al. 2022; Sharma et al. 2022; Spanaki et al. 2021). However, we believe it to have theoretical implications for other industries that transform towards greater integration of embodied AI, such as healthcare or maintenance or even industrial production. A third limitation is that business model dynamics involving embodied AI resemble digital transformation challenges. Our framework foregrounds datafication, platforms, and recurring monetization, but the feasibility of these logics depends on uneven connectivity, repair and service capacity, and the availability of high-quality training data. Where these conditions are weak, the shift from episodic transactions to continuous

workflows may stall or take different forms. Yet, the emergence of business model dynamics reflects the extent to which it is driven by management-led AI initiatives versus gradual, evolutionary adaptations of the existing model (Jorzik et al. 2024).

Several research opportunities follow directly. Future work can empirically validate and refine the logic by treating the grid as a measurement scheme. Studies could analyze firms and offerings according to activity content, activity structure, and governance choices, then test whether configurations predict adoption, profitability, resilience, or sustainability outcomes. Integrating AI with physical action intensifies data, platform, and capability concerns. Ensuring safety, real-time human–machine coordination, and scalability requires adaptive service design, integrated hardware-software–human systems, and robust ecosystem orchestration. Longitudinal research is especially important because embodied AI business models evolve through sequencing, learning, re-design, and lock-in. Panel designs could trace how recurring revenue architectures emerge from installed bases, how retrofit pathways change diffusion speed, and how shifts in data access rules redistribute value capture over time. Comparative research across institutional contexts can illuminate when openness versus control becomes the dominant equilibrium. This encompasses the influence of interoperability standards, right-to-repair policies, subsidy programs, and data governance regulations on both innovation incentives and farmers' reliance on technology. Traditional digital concerns such as data governance, platform strategy, and capability development, are amplified by richer sensor data, higher switching costs, and the need for real-time human–machine coordination and operational guarantees in embodied AI. Integrating AI into business models then requires careful attention to ethical and societal considerations than purely technical or economic objectives (Bronson 2018). Research must therefore address data privacy, bias, accountability, transparency, regulatory compliance (Breidbach & Maglio 2020), equity concerns and how inclusive processes align innovation trajectories with ethical agricultural transformation (Bronson 2018).

A second promising stream focuses on micro-foundations and sociotechnical fit. Our framework is based on the premise that value is generated for farmers. Micro-foundations such as routines, capabilities, and actor interactions shape how resources are mobilized and value is created (Wuebker et al. 2023). Misalignment of perceptions among stakeholders regarding value, priorities, or technology can hinder innovation by creating conflicting expectations and governance challenges. Thus, understanding business model dynamics requires attention not only to design and strategy but also to the cognitive and social processes that influence implementation.

Our framework further assumes continuous workflows, but realization depends on farmers' capabilities, AI literacy, trust, and local practices, as well as on the reliability of automation in variable field environments. Research can examine how training, advisory networks, and dealer capabilities mediate value delivery, and how failure modes, downtime, and uncertainty affect the willingness to pay for subscriptions or outcome-based contracts. Another stream can examine ecosystem governance more directly by studying complementors, API design, app marketplaces, and contracting terms. Work that links governance choices to complement innovation rates, switching costs, and bargaining outcomes would sharpen the power asymmetries to be expected.

Future research should also explore how entrepreneurial orientation (EO) moderates the impact of AI-driven initiatives on business model dynamics, distinguishing between radical, management-led transformations and gradual, evolutionary adaptations and how that allows to deal with environmental dynamics (Bouncken & Ratzmann 2026). Additionally, investigating EO's role in translating incremental AI adoption into sustained competitive advantage can provide insights into how firms leverage innovation capabilities over time. Finally, sector-specific analyses could reveal how EO interacts with ecosystem dynamics to shape the effectiveness of AI-enabled business model changes.

Key future research questions concern AI based changes on collaboration (Bouncken & Vogt 2025), co-opetition, and co-innovation (Bouncken & Vogt 2026; Klimas & Czakon 2022) across vertically, horizontally, and spatially embedded networks (Bichler et al. 2021; Cesinger et al. 2016), and how these dynamics shape the scaling, safety, and responsiveness of (embodied) AI-driven business models in physically and digitally embedded environments. Future research could also explore how key systemic tensions unfold within ecosystems, particularly in contexts where actors are interdependent yet pursue divergent objectives or are subject to different digital identities (Bouncken & Barwinski 2021; Czakon et al. 2024). Additionally, studies could examine how these tensions evolve across co-innovation stages and how ecosystem governance mechanisms mediate their impact on value creation and knowledge sharing.

Finally, future research can broaden outcomes beyond firm performance by analyzing distributional and societal effects, including labor substitution and skill upgrading, data rights and privacy, environmental externalities, and the fairness of outcome-based schemes under climate volatility.

7 Conclusion

Our conceptual study advances the emerging conversation on embodied AI by showing that it introduces a fundamentally new logic of business model dynamics. Unlike disembodied AI, which primarily enhances analytics or decision support, embodied AI refers to intelligent systems in which cognition, decision-making, and adaptation emerge through physical interaction with the environment. Business models no longer evolve through incremental digital enhancement alone, but through continuous interaction between technology, environment, and use. We develop two complementary models. Our transition model explains how business models move from asset-based, episodic logics toward adaptive, data-driven systems. Our integrative embodied AI business model grid then specifies how this transformation unfolds through changes in activity content, structure, and governance across interconnected ecosystems. We provide nine propositions that explicate how embodied AI shapes business model dynamics and systemic tensions inherent to closed-loop dynamics: namely openness versus control, scaling versus local fit, automation versus reliability, and monetization versus trust.

Using agriculture as a critical and revealing template, we explicate why embodied AI is especially consequential in traditional, asset-intensive industries characterized

by environmental variability, dependence on human expertise, and growing pressures for efficiency and sustainability. In this context, embodied AI shifts value from product performance toward continuous workflow optimization, lifecycle-based orchestration, and recurring, performance-linked revenue models.

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Authors and Affiliations

Ricarda B. Bouncken[1] · **Beate Cesinger**[1]

✉ Ricarda B. Bouncken
bouncken@uni-bayreuth.de

Beate Cesinger
beate.cesinger@gmail.com

[1] Department of Business Administration VI, Strategic Management and Organisation, University of Bayreuth, Bayreuth, Germany