# Phygital Agriculture: FruitScout and the Rise of Industry 4.0 in the Field

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*Agricultural unpredictability is addressed through FruitScout's phygital platform that harnesses inexpensive smartphones to create plant-level digital twins, bringing Industry 4.0 efficiencies.*

## SUMMARY

*Phygital systems integrate physical work and digital intelligence, transforming how organizations sense, plan, and act across complex, variable environments. Agriculture remains among the least digitized production sectors, particularly in upstream operations, where variability in biological growth limits predictability and efficiency. This paper examines FruitScout, a smartphone-based computer vision platform that builds plant-level digital twins to generate prescriptive harvest and supply chain decisions. Drawing on insights from Industry 4.0, digital twin theory, and phygital integration, the paper develops a conceptual architecture for agricultural production systems. This architecture links five layers: enablers, operations, decisions, outcomes, and ecosystem. Using data from agave production, the case illustrates how phygital instrumentation reduces state uncertainty and enables adaptive planning. The conclusion contrasts software-centric and hardware-intensive approaches to agricultural digitization, highlighting managerial trade-offs in scalability, accuracy, and capital intensity.*

**Keywords**: phygital agriculture, industry 4.0, agricultural production systems, FruitScout

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## *Introducing Phygital Agriculture*

Over the past decade, organizations have increasingly sought to bridge the divide between the tangible operations of production systems and the expanding power of digital intelligence. This convergence, sometimes described as phygital integration, has become a defining feature of the fourth industrial revolution [1,2].

Phygital systems embed sensors, connectivity, and analytics within physical processes, creating continuous feedback loops that enhance decision-making and performance [3]. While this transformation is advanced in sectors such as manufacturing, logistics, and retail, agriculture has lagged behind. Biological variability, fragmented supply chains, and capital constraints have limited the widespread diffusion of digital intelligence in farming operations [4,5]. Yet agriculture faces mounting pressure to improve productivity, reduce input waste, and increase resilience amid climate uncertainty and shifting global demand.

This article addresses this gap by proposing phygital agriculture: a paradigm that merges field-level biological processes with data-driven, digital systems. The study focuses on FruitScout, a U.S.-based technology company that uses computer vision and artificial intelligence to convert smartphone images into plant-level measurements, effectively constructing digital twins of crops. By digitally instrumenting physical growth processes, the company enables more precise yield estimation, resource allocation, and harvest scheduling. Through this lens, agriculture becomes not merely a biological endeavor but a digitally augmented production system [6].

Despite the increasing attention to "smart farming" and "precision agriculture," much of the literature emphasizes either the technological tools themselves or their potential for sustainability [7]. Less attention has been paid to how digital and physical components integrate operationally; that is, the phygital mechanisms that convert raw data into prescriptive decisions. Moreover, the managerial and organizational implications of such systems remain underdeveloped. This article, therefore, contributes to both scholarship and practice by articulating a theoretical and applied framework for understanding how phygital architectures operate in biological production contexts.

The study's contributions are threefold. First, it offers a conceptual architecture that specifies how phygital systems create and circulate value through layered processes of sensing, data modeling, decision support, and ecosystem coordination. Second, it provides an empirically grounded illustration through the FruitScout case showing how these layers manifest in practice and what economic and operational results they yield.

Third, it identifies the boundary conditions (technological, ethical, and ecological) that shape the responsible scaling of such systems. The aim is to produce insights accessible to both researchers and practitioners seeking to implement or govern digital transformations in resource-dependent sectors.

The remainder of this article proceeds as follows. The next section reviews relevant literature on phygital systems, Industry 4.0, and digital twins, situating agriculture within this evolving discourse. It is followed by a conceptual framework outlining the architecture of phygital biological production. The case analysis then explores how this architecture operates through FruitScout's system. The conclusion discusses hardware-intensive and software-centric models of digital agriculture and related issues.

> ***Phygital agriculture transforms farming from a biological endeavor into a phygitally augmented production system, which is resilient, sustainable, and human-centered.***

## *Rethinking Digital Integration in Agriculture*

The concept of phygital can be conceptualized as the purposeful fusion of digital capabilities with physical systems to create closed-loop sensing, analysis, and action. Rather than layering digital tools on top of existing operations, phygital systems embed sensors, software, and data models into everyday routines so that the digital layer continually reflects and shapes the physical one [8] . This extends the logic of smart, connected products [9] from discrete assets to end-to-end workflows, emphasizing performance gains that arise from optimized processes rather than from data availability alone.

These developments unfold within the broader context of Industry 4.0, which integrates cyber-physical systems, automation, connectivity, and analytics into a new production paradigm [10]. Research highlights enabling technologies such as IoT, edge computing, cloud platforms, and AI, as well as organizational capabilities such as interoperability, governance, and change management, as elements required to capture value [11]. Applying these factory-based logics to biological environments remains difficult. Agricultural production is path-dependent, climatologically driven, and heterogeneous across terroir, complicating standardization and quality control, which are hallmarks of Industry 4.0 in controlled manufacturing settings.

Within this paradigm, digital twins, virtual representations of physical entities synchronized through continuous data flows, have become central to digital manufacturing and increasingly relevant to agriculture [12]. A twin's managerial usefulness depends on fidelity, refresh rate, and controllability. Agriculture challenges these conditions: measurement is costly at scale, variability is high, and connectivity can be unreliable. Emerging advances in computer vision and edge AI can lower sensing costs by using smartphone cameras to infer plant-level states, supporting more dynamic and affordable digital twins that reach beyond the factory context [13].

The precision-agriculture literature documents efficiency and sustainability gains from GPS guidance, variable-rate inputs, UAVs, and farm-management systems, while also noting adoption barriers tied to cost, data ownership, and farmers' values [14].

A phygital perspective extends this research by emphasizing integration—how sensing becomes part of daily labor, how measurements inform operational plans, and how those plans align with downstream processing and logistics—so that digital layers actively drive action rather than merely inform it. Rather than deploying proprietary sensors and dedicated technology, firms can "instrument" and augment labor by embedding measurement capabilities into existing workflows through general-purpose devices such as smartphones. This approach ties digital-twin refresh rates to work cadence, reducing capital intensity but creating managerial challenges around training, incentives, and data governance. Aligning measurement with field rhythms and standardizing outputs via AI can transform heterogeneous observations into reliable signals, though this raises issues of privacy and benefit-sharing that critical scholarship has highlighted [15].

Another emerging shift concerns the analytical objectives of agricultural systems. Many technologies stop at dashboards and alerts (monitoring), while fewer deliver prescriptions that sequence work or allocate resources in real time. As crop twins gain fidelity and timeliness, they can underpin planning decisions such as optimized harvest scheduling, balancing ripeness with processing throughput, and routing logistics to minimize waste [16,17]. This move, from monitoring to prescription, introduces design demands: models must encode within-field heterogeneity, estimate readiness windows, align supply-chain constraints, and remain interpretable for managers.

Phygital agriculture also unfolds within ecosystems that span growers, processors, suppliers, logistics providers, and technology vendors. Data flows across organizational boundaries generate both network effects and frictions.

Platform-oriented perspectives highlight how value accrues when usage improves models that, in turn, attract more usage—while also illustrating how switching costs and vendor dependence can arise [18,19]. Governance choices around APIs, auditability, portability, and outcome-linked pricing shape adoption incentives and the distribution of benefits. The literature points to a persistent tension between proprietary advantage—differentiated models trained on captive data—and sectoral efficiency through interoperability and shared standards, a tension that is particularly acute in perishable, thin-margin agri-food systems [20].

Together, these strands reveal three gaps. First, there is a lack of a process model tailored to biological production that links labor-embedded sensing, twin fidelity and refresh rates, decision layers, and economic outcomes. Second, limited work shows how phygital loops generate prescriptive plans that synchronize field conditions with processing capacity. Third, managerial guidance remains fragmented on when software-centric, low-cost approaches outperform hardware-heavy strategies, and on how governance and ethics should be embedded into system design from the outset [21].

## *A Framework for Phygital Architecture in Biological Production Systems*

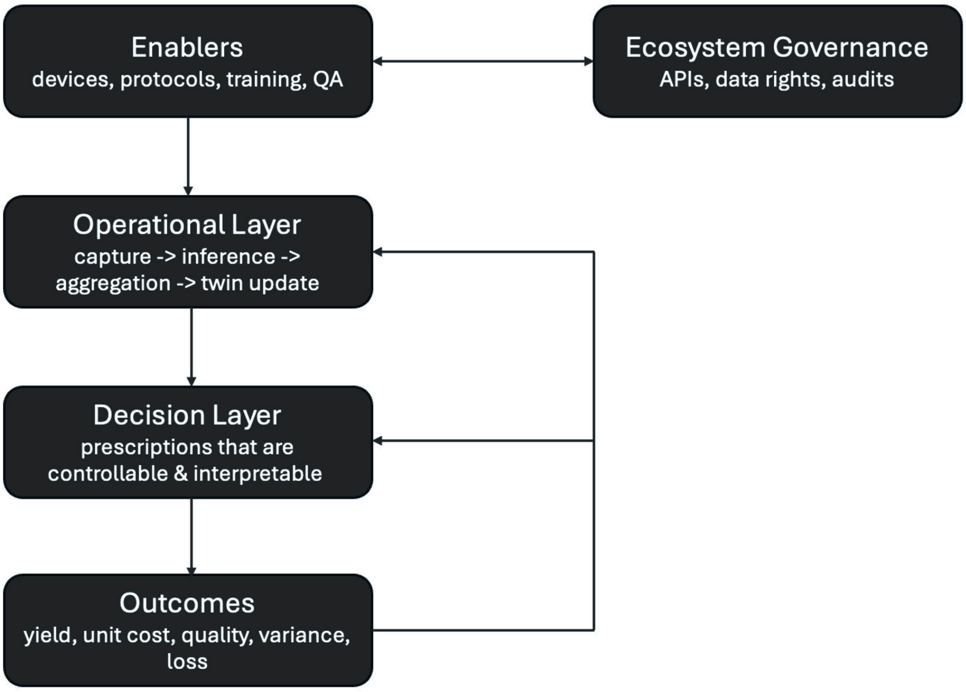
This section develops a process-oriented architecture that explains how phygital systems generate value within biological production contexts. The framework (**see Figure 1**) specifies five layers: enablers, operational loop, decision layer, outcomes, and ecosystem dynamics. The goal is to make explicit the mechanisms by which digital intelligence becomes embedded in routine fieldwork and supply-chain planning, rather than treating technology as an adjunct to existing practices [22]. While the architecture draws on established insights from Industry 4.0 and digital twins, it adapts them to settings where the state of the system is a living organism and measurement is both noisy and intermittent [23].

The first layer concerns enabling conditions. In agriculture, the cost of dense, fixed instrumentation can be prohibitive; connectivity is often intermittent. The framework therefore emphasizes general-purpose, low-capital technologies such as smartphones that can be woven into workers' routines operating in an off-line, edge independent manner. By aligning data capture with normal field tasks such as scouting or pruning, labor and measurement can be integrated. This alignment matters because it determines the fidelity and refresh rate of the digital twin, which in turn influences how quickly decisions can adjust to changing biological conditions. Enablers thus include consumer hardware and enabling software, as well as training, incentives, and quality assurance practices that make field measurements practical and reliable at scale [24].

The second layer is the operational loop that converts raw observations into reliable state estimates and forecasts. In this loop, images or other inputs are captured in the field, processed through machine-learning models, and aggregated to update plot- or plant-level representations. Three construct-level properties govern the managerial usefulness of this loop. Fidelity describes how accurately the model captures the states most relevant to decisions such as readiness, quality, risk, or expected yield. Refresh rate captures the temporal frequency of updates, which is critical in perishable contexts where short windows of optimal action exist. Latency refers to the time between capture and availability of actionable estimates, which depends on both computational arrangements and workflow design. When fidelity is adequate, refresh rates are aligned with biological dynamics, and latency is low, the twin's state approximates what managers would find if they were physically present at scale and at the moment of decision [25].

The third layer translates state estimates into prescriptions. In manufacturing, digitally connected systems can adjust setpoints or reschedule tasks rapidly; in agriculture, prescriptions must respect growth trajectories and the constraints of downstream processing.

**Figure 1.** The phygital architecture framework for biological production (process and feedback)




The architecture therefore models decision-making as an integration problem: field states must be synchronized with processor capacity, labor availability, logistics, and quality requirements. The decision layer transforms a continuously updated map of biological readiness into prioritized, time-bounded work orders that schedule interventions, sequence harvests, and route shipments. Controllability or the practical ability to act on recommendations is essential. Prescriptions that cannot be executed due to equipment, labor, cost, or contractual limits erode trust and adoption. Consequently, the framework positions the decision layer not as a purely computational optimizer but as a socio-technical interface that must produce plans that are feasible, interpretable, and aligned with managerial accountability [26,27]. The fourth layer focuses on outcomes and measurement of value. In phygital agriculture, leaders tend to track a small set of performance indicators: yield realized versus forecast, unit cost, variability in quality, and losses attributable to mis-timed harvests or logistics failures.

The framework links these outcomes causally to improvements in information quality and timing. When digital twins reduce state uncertainty and synchronize operations, managers can narrow readiness windows, balance processing lines more effectively, and mitigate waste. Because many agricultural contexts involve thin margins and volatile supply, even modest improvements in predictability can compound across procurement, scheduling, and inventory management. However, the framework also stresses transparency: claims about yield or cost must be accompanied by data provenance, validation status, and contextual limits so that decision makers can interpret effect sizes cautiously and avoid overgeneralization [28].

The fifth layer addresses ecosystem dynamics. Data created by labor-embedded sensing and prescriptive planning often cross firm boundaries, involving growers, processors, distributors, and technology providers. As usage expands, models may improve through exposure to diverse field conditions, creating positive feedback that attracts further adoption.

At the same time, these network effects can produce switching costs and concerns over data rights, portability, and bargaining power. The framework therefore treats governance (APIs, access controls, auditability, and pricing models tied to outcomes) as a design choice that shapes long-run diffusion and fairness. In agriculture, where trust and relationships are central, governance decisions can determine whether phygital systems become sectoral utilities or remain proprietary islands [29].

The above-mentioned layers form a closed loop. Enablers determine the cost and cadence of sensing; the operational loop determines the quality and timeliness of state estimates; the decision layer transforms those estimates into feasible prescriptions; outcomes provide feedback that recalibrates models and workflows; and ecosystem choices condition adoption, learning, and value distribution.

The framework offers three testable implications: First, when measurement is embedded in routine labor using commodity devices, organizations can achieve higher refresh rates at lower capital expense, which should increase the responsiveness of plans to biological variation. Second, when prescriptions explicitly integrate downstream capacity constraints with plant-level readiness, realized performance should improve not because of better averages but because of better timing. Third, when governance ensures data portability and transparent attribution of value, adoption should be broader and models should generalize better, even if short-run proprietary advantage is diluted.

## *Operationalizing Phygital Architecture: Insights from the FruitScout Case*

FruitScout illustrates a software-centric, low-capital path to phygital agriculture (**see Table 1**). Using commodity smartphones to capture plant images at scale, machine learning to infer biologically meaningful states, and a continuously updated field-level digital twin, the system drives prescriptive harvest and supply-chain decisions.

By embedding measurement into routine fieldwork, it converts dispersed, anecdotal observations into standardized, actionable data: essentially adapting Industry 4.0’s cyber-physical integration to biological contexts where measurement is sparse and noisy [30].

The enabling layer relies on general-purpose devices, not proprietary hardware. Crews follow simple capture protocols supported by in-app prompts. Managerially, this lowers capital cost and change-management friction because tasks resemble familiar scouting and quality checks. System accuracy hinges less on dense, fixed sensors and more on workflows that elicit consistent human observations; consequently, the cadence of work becomes the cadence of measurement—precisely what phygital frameworks predict when labor is instrumented with commodity tools [31].

Operationally, raw images are translated into a decision-ready crop representation. Detected features (e.g., counts, size, growth rate, maturity) are aggregated from plant/row to block/field, updating the digital twin on a rolling basis. Managerial reliability rests on fidelity (capturing phenology and quality-relevant attributes), refresh rate (driven by how often crews revisit plots), and latency (edge/on-device versus cloud inference given rural connectivity). Bounding latency with lightweight models and local buffering helps estimates arrive in time for daily/weekly planning, making the “map” approximate what supervisors would see if walking every row [32].

The decision layer is designed for interpretability and controllability. Instead of a dashboard alone, the platform produces prioritized work orders that sequence harvests by plot and date while accounting for growth-rate variability, labor, equipment limits, processor capacity, logistics, and contractual constraints. Supervisors can audit recommendations down to images and model outputs, supporting accountability and organizational learning [33]. Early adopter narratives point to improvements in realized yield, unit cost, and quality variability via two mechanisms: tighter timing of harvest to biological readiness and better synchronization between field inflow and factory throughput.

**Table 1.** How FruitScout illustrates the layers of the phygital architecture

| Layer | What FruitScout Does | Manager Actions (Levers) | Metrics to Monitor |
|---|---|---|---|
| **Instrumentation (Sensing-in-Work)** | Uses smartphones and simple photo protocols to turn routine fieldwork into measurement points, avoiding dense proprietary sensors. | Standardize capture protocols; train and coach crews; set incentives and quality control; monitor performance; ensure device support. | Image coverage, capture quality pass rate, cost per measured acre, crew compliance. |
| **Data and Model (Digital Twin Maintenance)** | Computer vision/ML infers counts, size, growth rate and maturity; aggregates from plant to field; updates the digital twin continuously. | Set targets for fidelity, refresh rate, and latency; choose edge/on-device vs. cloud inference; plan offline buffering. | Model error, days between revisits, time from capture to recommendation. |
| **Decision and Control (Prescription Engine)** | Generates prioritized harvest work orders by plot/date; accounts for labor, equipment, capacity, and logistics. | Define capacity constraints; ensure interpretability and audit trails; integrate with scheduling systems. | Recommendation execution rate, plan adherence, replan frequency, audit rate. |
| **Execution and Outcomes** | Aligns harvest timing with readiness and synchronizes field inflow with processing throughput. | Run weekly reviews; close loop with post-hoc checks; adjust thresholds and readiness windows. | Realized yield, unit cost, quality variance, overtime/idle time, loss/waste. |

Reduced readiness error (too early/too late) and steadier inflow can lower overtime, idle time, and quality loss, effects consistent with a shift from descriptive monitoring to prescriptive planning. However, impacts are enterprise-reported and context-specific; effect sizes should be interpreted cautiously [34].

Adoption dynamics highlight ecosystem considerations. As more fields are instrumented, exposure to diverse morphology, geological diversity, and microclimates can improve model accuracy, creating data network effects: usage produces better models, which drive better prescriptions, which in turn drive more usage. Governance remains pivotal: clarity on ownership of raw images and derived features, data-sharing across organizational boundaries, APIs/export formats, audit trails, and outcome-linked pricing can either build trust for multi-party coordination or create switching costs [35].

For example, limited data portability can lock growers into vendor ecosystems, undermining their autonomy and creating unequal power dynamics with technology providers [36]. To mitigate these issues, the decision layer prioritizes inclusive design and equitable data governance to ensure technological advancements benefit all parties without perpetuating social inequities [37].

Managerially, three lessons stand out. First, embedding sensing in familiar work can expand coverage at low cost, but requires investment in training, incentives, and quality control to keep data reliable. Second, prescriptions that align field readiness with downstream capacity outperform "harvest when ready" heuristics by optimizing the whole chain. Third, governance and transparency are strategic levers: clear provenance, interpretable recommendations, and pricing tied to outcomes often matter more for adoption than marginal gains in model accuracy [38]

## *Conclusion*

This article has argued that phygital agriculture is best understood not as a collection of tools but as an architecture that embeds digital intelligence into routine fieldwork and connects upstream biological variability to downstream operational decisions.

By specifying five layers (enablers, the operational loop, the decision layer, outcomes, and ecosystem dynamics) we clarified how information moves from labor-embedded sensing to prescriptive action and measurable value. The FruitScout case illustrates a software-centric path that leverages commodity smartphones and computer vision to maintain plant-level digital twins of production fields, convert state estimates into feasible work orders, and synchronize harvest timing with processing capacity. The managerial contribution is a process model that leaders can use to diagnose bottlenecks, design workflows, and prioritize investments, emphasizing that performance gains come from orchestrating sensing cadence, model fidelity, and controllability rather than from technology in isolation [39,40].

Theoretically, the analysis links phygital integration to core constructs in Industry 4.0 and digital twin research while adapting them to the realities of biological systems [41]. It distinguishes software-centric approaches from hardware-heavy alternatives, arguing that fit depends on crop biology, operational rhythms, and the economics of downstream assets.

In contexts with visually inferable cues and repeatable field tasks, embedding sensing into labor can yield higher refresh rates at lower capital intensity, enabling prescriptions that reduce losses from mistimed harvests and uneven factory inflow. Where continuous telemetry or non-visual traits are essential, specialized sensors remain indispensable.

***Phygital agriculture embeds intelligence, connects biology, and balances responsibility.***

The core implication is that managers should design portfolio strategies that combine a broad, low-cost coverage layer with targeted precision layers where marginal fidelity is worth the cost [42]. The analysis also surfaces governance as a first-order design choice. Because usage improves models and models influence work, data rights, portability, and pricing structures shape adoption incentives and the distribution of value across growers, processors, and technology providers.

Phygital systems that offer interpretable recommendations, transparent provenance, and outcome-linked pricing will earn trust more quickly than black-box platforms, especially in sectors where margins are thin and relationships are long term [43]. Responsible scaling likewise requires attention to labor practices, algorithmic bias, and rural connectivity so that digital gains do not exacerbate existing inequities. By foregrounding these socio-technical issues within the architecture, the paper contributes a balanced account of opportunities and risks.

In terms of generalizability, the transferability of FruitScout's phygital model hinges on crop biology, harvesting cycles, and supply chain dynamics, offering scalability in low-capital contexts but with limitations. For crops like agave or apples with extended growth periods and visually inferable traits, the smartphone-based approach enables effective intermittent monitoring and digital twin updates, aligning well with fragmented supply chains [44]. In contrast, short-cycle perishables such as strawberries demand continuous sensing to mitigate waste in tight logistics, potentially necessitating hardware integration and reducing the model's cost advantages [45]. Addressing these variances through modular adaptations could enhance cross-crop applicability while preserving sustainability gains [46].

ooking forward, further research is needed in three areas. First, empirical studies should examine how phygital models perform across different crops, geographies, and organizational contexts, especially among smallholder farmers who face unique constraints.

Second, longitudinal studies are required to evaluate not only immediate financial outcomes but also long-term impacts on sustainability, labor relations, and rural development [47]. Third, scholars should investigate how phygital platforms intersect with climate adaptation agendas, since digital twins offer a promising way to anticipate and mitigate risks associated with weather variability and shifting ecological conditions [48].

## *Notes*

[**1**] Batat, W. (2024). What does phygital really mean? A conceptual introduction to the phygital customer experience (PH-CX) framework. Journal of Strategic Marketing, 32(8), 1220–1243.

[**2**] Schwab, K. (2017). The Fourth Industrial Revolution. Crown Business.

[**3**] Porter, M. E., and Heppelmann, J. E. (2014). How smart, connected products are transforming competition. Harvard Business Review, 92(11), 64–88.

[**4**] Bronson, K. (2019). Looking through a responsible innovation lens at agricultural big data. NJAS – Wageningen Journal of Life Sciences, 90–91, 100294.

[**5**] Rose, D. C., and Chilvers, J. (2018). Agriculture 4.0? Envisioning future agricultural systems: Critical social science perspectives. Frontiers in Sustainable Food Systems, 2, 87.

[**6**] Kamilaris, A., and Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. Computers and Electronics in Agriculture, 147, 70–90.

[**7**] Wolfert, S., Ge, L., Verdouw, C., and Bogaardt, M.-J. (2017). Big data in smart farming – A review. Agricultural Systems, 153, 69–80.

[**8**] Batat (2024), op. cit.

[**9**] Porter and Heppelmann (2014), op. cit.

[**10**] Schwab, K. (2017). The Fourth Industrial Revolution. Crown Business.

[**11**] Porter and Heppelmann (2014), op. cit.

[12] Tao, F., Qi, Q., Liu, A., and Kusiak, A. (2022). Data-driven smart manufacturing. Journal of Manufacturing Systems, 62, 738–752.

[**13**] Kamilaris and Prenafeta-Boldú (2018), op. cit.

[**14**] Wolfert, Verdouw and Bogaardt (2017), op. cit.

[**15**] Bronson (2019), op. cit.

[**16**] Purcell, W., and Neubauer, T. (2023). Digital twins in agriculture: A state-of-the-art review. Smart Agricultural Technology, 3, 100094.

[**17**] Knibbe, W. J., Afman, L., Boersma, S., Bogaardt, M.-J., Evers, J., Van Evert, F., Van der Heide, J., Hoving, I., Van Mourik, S., De Ridder, D., and De Wit, A. (2022). Digital twins in the green life sciences. NJAS: Impact in Agricultural and Life Sciences, 94(1), 249–279

[**18**] Porter and Heppelmann (2014), op. cit.

[**19**] Wolfert et al. (2017), op. cit.

[**20**] OECD. (2020). Issues around data governance in the digital transformation of agriculture: The farmers' perspective(Food, Agriculture and Fisheries Papers No. 146). OECD Publishing.

[**21**] Bronson (2019), op. cit.

[**22**] Porter and Heppelmann (2014), op. cit.

[**23**] Schwab (2017), op. cit.

[**24**] Kamilaris, A., Kartakoullis, A., and Prenafeta-Boldú, F. X. (2017). A review on the practice of big data analysis in agriculture. Computers and Electronics in Agriculture, 143, 23–37.

[**25**] Tao et al. (2022), op. cit.

[**26**] Porter and Heppelmann (2014), op. cit.

[**27**] Wolfert et al. (2017), op. cit.

[**28**] Rose and Chilvers (2018), op. cit.

[**29**] Wolfert et al. (2017), op. cit.

[**30**] Schwab (2017), op. cit.

[**31**] Kamilaris et al. (2017), op. cit.

[**32**] Tao et al. (2022), op. cit.

[**33**] Wolfert et al. (2017), op. cit.

[**34**] Rose and Chilvers (2018), op. cit.

[**35**] Wolfert et al. (2017), op. cit.

[**36**] OECD (2020), op. cit.

[**37**] Bronson (2019), op. cit.

[**38**] Tao et al. (2022), op. cit.

[**39**] Porter and Heppelmann (2014), op. cit.

[**40**] Tao et al. (2022), op. cit.

[**41**] Schwab (2017), op. cit.

[**42**] Wolfert et al. (2017), op. cit.

[**43**] Bronson (2019), op. cit.

[**44**] Manivasagam, V. S. (2025). From Bytes to Farm: Transferability of Industrial Digital Twins in Agricultural Systems. Journal of Biosystems Engineering, 50(1), 130–144.

[**45**] Tzachor, A., Richards, C. E., and Jeen, S. (2022). Transforming agrifood production systems and supply chains with digital twins. NPJ Science of Food, 6(1), 47.

[**46**] Purcell and Neubauer (2023), op. cit.

[**47**] Carbonell, I. M. (2016). The ethics of big data in agriculture. Internet Policy Review, 5(1).

[**48**] Liakos, K. G., Busato, P., Moshou, D., Pearson, S., and Bochtis, D. (2018). Machine learning in agriculture: A review. Sensors, 18(8), 2674.

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## Disclosure of AI tool use

The authors used Google's AI-assisted search for literature review and Microsoft Copilot for grammar support.

## Author Biographies

***Dr. Philip DesAutels*** is Chief Product Officer at FruitScout, a firm that leverages advance computer vision and AI technologies to create digital twins of large-scale agricultural concerns to deliver industrial 4.0 process management technologies to agricultural production. Prior to FruitScout, he was CTO at LQD WiFi where he took the Palo Smart City kiosk from idea to product, a product which was sold to Verizon. Philip served as the Executive Director of IoT at the Linux Foundation for 3 years where he led multiple global open-source projects and advocated for a safe, secure and private connected world. He co-founded Xively, the first commercial IoT platform which was sold to Google. Philip holds a BSc and MSc in Industrial and Management Engineering from Rensselaer Polytechnic Institute, a PhD from Luleå University of Technology in Sweden. He has authored numerous academic papers, on topics ranging from mathematics to marketing, publishing in top peer-reviewed business journals such as Business Horizons, Journal of Public Affairs, Psychology and Marketing, The Journal of Strategic Information Systems, and the International Journal of Technology Marketing. In addition, Philip holds multiple patents in the IoT domain, and sports an Erdös number of 3.

***Dr. Pierre Berthon*** holds the Clifford F Youse Chair of Experience Design, Marketing and Strategy at Bentley University. Professor Berthon has held academic positions at Columbia University in the US, Henley Management College, Cardiff University and University of Bath in the UK. He has also taught or held visiting positions at Rotterdam School of Management, Copenhagen Business School, Norwegian School of Economics and Management, Cape Town Business School, University of Cape Town and Athens Laboratory of Business Administration. His research focuses on the interaction of technology, corporate strategy and consumer behavior, and has appeared in journals such as Sloan Management Review, California Management Review, Information Systems Research, Technological Forecasting and Social Change, Journal of the Academy of Marketing Science, Journal of Business Research, Journal of International Marketing, Long Range Planning, Business Horizons, European Management Journal, Journal of Interactive Marketing, Journal of Information Technology, Information Systems Review, Journal of Business Ethics, Marketing Theory and others, with over 200 papers published in peer reviewed journals.

***Dr. Tamara Rabinovich*** is a Senior Instructional Technologist and Designer at Quincy College (USA) with more than two decades of experience in hybrid education, instructional design, and the evaluation of online and technology-enhanced learning programs. She has over 25 years of teaching experience at the undergraduate and graduate levels, with academic expertise spanning Computer Science, Educational Technology, User Experience Design, and Business Statistics. Dr. Rabinovich earned her B.A. in Computer Science from the University of Haifa, an M.S. in Science and Technology Education from the Technion – Israel Institute of Technology, and an Ed.D. in Educational Media and Technology from Boston University. Her research examines the intersection of emerging technologies, distance education, digital misinformation, and the evolving impact of artificial intelligence on business, education, and organizational decision-making. Her work has been published in leading peer-reviewed journals, including Business Horizons, Quarterly Review of Distance Education, Journal of Product and Brand Management, International Journal of Technology Marketing, and the Journal of Financial Services Marketing. She has presented her research at international conferences such as eLearn (World Conference on Educational Technology) and the Hawaii International Conference on System Sciences (HICSS).

# Phygital Business Review

## Winter Collector Issue

## **Phygital Ecosystems: Adapt or Die**

# Phygital Business Review

*2026 WINTER COLLECTOR ISSUE*

**PHYGITAL ECOSYSTEMS: ADAPT OR DIE**