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Digital phenotyping as an integrative framework for engineering and life science approaches in agro-ecosystems

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Abstract

Digital phenotyping has evolved from simple imaging-based trait measurement to a core technology enabling large-scale analysis of genotype × environment × management (G × E × M) interactions. This review highlights the manner in which digital phenotyping simultaneously supports two major research trajectories in modern agro-ecosystems. In engineering-driven approaches, imaging and sensor data are increasingly used to enhance the physical control of climate, irrigation, and crop protection through model-based and AI-assisted decision systems. In life science-centered approaches, high-throughput phenotyping and multi-omics integration provide mechanistic insights into plant stress responses, developmental plasticity, and complex trait regulation. Despite significant progress, both pathways face limitations in addressing the biological complexity and climatic unpredictability of crop systems. We discuss the emerging opportunities to integrate these domains through a two-layer AI framework that combines real-time sensing and actuation ("Physical AI") with ontology- and LLM-based reasoning systems capable of synthesizing biological knowledge and generating strategic policies. Together, these developments position digital phenotyping as a bridging technology and a foundation for adaptive, resilient, and knowledge-driven agro-ecosystem management.

Keywords

digital phenotyping, physical artificial intelligence, plant image science, ontology-based reasoning

Introduction

Digital phenotyping has emerged as an imaging-based approach for quantifying plant traits and monitoring plant growth in breeding programs (Li et al. 2014). Advances in sensors, automation, and computation have expanded these methods to modern phenomics, supporting the large-scale analysis of genotype × environment × management (G × E × M) interactions (Fiorani and Schurr 2013; Yang et al. 2020).

Currently, digital phenotyping supports two major research trajectories. Engineering-driven approaches use imaging and sensing technologies to enhance precision crop protection, environmental control, and simulation-based cultivation strategies (Mahlein 2016). In parallel, life science-centered approaches use phenomics and multi-omics integration to understand stress responses and identify the genetic factors underlying complex traits (Araus and Cairns 2014).

Although both domains have advanced significantly, increasing climatic variability and

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narrowing crop genetic diversity have highlighted their limitations when applied independently (Yang et al. 2020). Importantly, both rely on digital phenotyping as a shared source of quantitative and scalable measurements for monitoring plant responses and validating biological hypotheses (Pieruschka and Schurr 2019).

This review summarizes global developments in engineering- and life science-oriented approaches, emphasizes digital phenotyping as a bridging technology, and discusses the pathways for integrating phenomic data and computational methods to manage complex agro-ecosystems.

Engineering-driven approach: evolution and limitations of physical control

Digital phenotyping is currently central to engineering-driven systems because it provides quantitative indicators of the canopy structure, stress responses, and water-use dynamics that inform climate and irrigation management (Li et al. 2014). As imaging quality improved, phenotyping enabled the earlier detection of stress and more plant-centered control strategies (Mahlein 2016; Pieruschka and Schurr 2019).

Recent developments have integrated phenotyping with environmental and soil data to support artificial intelligence (AI)-assisted forecasting of yield, evapotranspiration, irrigation needs, and microclimatic conditions (van Klompenburg et al. 2020). Imaging-based disease and nutrient diagnosis further enhance precision interventions. Digital phenotyping has also contributed to the development of simulation-based control and early digital-twin applications (Table 1).

Table 1. Representative digital phenotyping technologies used in engineering-driven physical control

Digital phenotyping technology	Target crops	Physical control objective	References
RGB imaging	Tomato, cucumber, lettuce	Growth estimation, early stress detection, climate/irrigation adjustment	Li et al. (2014); Pieruschka and Schurr (2019)
Hyperspectral imaging	Wheat, barley, maize	Disease/nutrient diagnosis, precision spraying	Mahlein (2016)
Thermal imaging	Greenhouse tomato, grapevine	Water use monitoring, irrigation scheduling	Khan et al. (2019)
3D / LiDAR	Tomato, pepper, fruit crops	Canopy modeling, robotics, forecasting	Paulus (2019)

RGB, red-green-blue; 3D, three dimensions; LiDAR, light detection and ranging.

However, the physical control frameworks face persistent constraints. High installation and operational costs limit their adoption beyond high-tech systems (Wang et al. 2025). AI models require large, high-quality datasets and often struggle during rare or extreme weather events (Materia et al. 2024). Most engineering approaches remain environment-centric and do not explicitly account for plant physiological mechanisms or G × E × M interactions, thereby reducing their robustness under multi-stress scenarios (Yang et al. 2020). Growers also maintain manual overrides because of concerns regarding transparency and reliability.

Moreover, current physical-control architectures are optimized for short-term environmental responses and rarely incorporate biological objectives such as resilience or long-term trait expression. Digital phenotyping can help expand these frameworks by providing plant-level signals that link control actions to physiological outcomes; however, this potential remains underutilized. These limitations underscore the need to couple engineering systems with biologically informed reasoning-capable frameworks.

Life science-centered approaches: Genome-to-phenome understanding and its limitations

Life science-centered research aims to explain the manner in which genetic variations interact with the environment and management to produce phenotypes. Traditional multi-environment regional trials quantified G × E interactions for major traits such as yield and stress tolerance but provided limited temporal resolution (Hoyos-Villegas et al. 2025).

High-throughput phenotyping (HTP) has transformed this process by enabling dynamic, nondestructive measurement of morphological and physiological traits through RGB, hyperspectral, thermal, and 3D imaging (Li et al. 2021; Zhao et al. 2019). Field-based HTP using UAVs and ground systems further supports large-scale G × E assessments (Xu and Li 2022; Adak et al, 2024).

Multi-omics integration—transcriptomics, metabolomics, and proteomics—has added mechanistic insight into the regulatory networks underlying complex traits (Younas 2025). Recent efforts have incorporated environmental and management metadata to extend analyses to G × E × M frameworks (Großkinsky et al. 2018) (Table 2).

Table 2. Summary of phenomics approaches in life science-centered research

Phenomics approach	Typical crops	Main objective	References
Controlled-environment HTP	Rice, wheat, barley, tomato	Growth dynamics, stress responses, genotype screening	Yang et al. (2020)
Field-based HTP (UAVs, ground robots, tractor-mounted sensors)	Cereals, legumes, maize	G × E trials, stress tolerance, yield prediction	Xu and Li (2022); Wang et al. (2025)
Multi-omics + phenomics integration	Mapping populations, breeding panels	Linking genes to traits, stress pathway mapping	Younas (2025)
Dynamic phenotyping (time-series phenotyping)	Model plants, cereals	Developmental dynamics, stress progression	Chang et al. (2021); Dhondt et al. (2014)

HTP, high throughput system; UAV, unmanned aerial vehicle; G × E, genotype × environment.

However, despite these advances, several challenges remain unresolved. HTP platforms require significant infrastructure and generate datasets that require intensive preprocessing (Sheikh et al. 2024). Multi-omics data provide mechanistic depth but limited predictive power for polygenic and environmentally sensitive traits. Field phenotyping remains affected by environmental noise, complicating its integration with controlled-environment observations. Translating phenomics and multi-omics outputs into breeding or management decisions remains slow.

However, digital phenotyping, offers a common quantitative layer that can support cross-environment harmonization, enabling AI models to connect molecular-level signals with field-relevant phenotypes. As G × E × M structures become more complex under climate variability, integrating life science insights with sensing, modeling, and AI systems will be essential to achieve scalable and context-aware biological decision-making.

Integrating physical AI with ontology–LLM knowledge systems

Physical AI systems—combining sensing, prediction, and actuation—enable the real-time monitoring and automated adjustment of climate, irrigation, and crop protection. However, they remain environment-centric and struggle to incorporate biological knowledge and long-term reasoning.

Ontology engineering and knowledge graphs offer structured representations of genes, traits, physiological processes, soils, and environments, thereby supporting a mechanistic understanding (Pech-May and Rios-Toledo 2023). Plant trait ontologies and phenotype knowledge bases facilitate standardized trait descriptions and improve the cross-study interpretation of genotype–phenotype relationships (Dumschott et al. 2023).

Large language models (LLMs) further enhance reasoning by synthesizing heterogeneous biological and environmental information. In medicine and biology, they have been used to generate hypotheses and interpret multimodal evidences (Singhal et al. 2023). Coupled with retrieval-augmented generation, LLMs can translate biological objectives into decision rules or scenario sets. In robotics, LLMs have supported translating abstract goals into procedural control instructions (Zeng et al. 2023).

In agriculture, ontology–LLM frameworks can define long-term utility functions—resilience, yield stability, and resource efficiency—

and translate them into rules that physical AI can operationalize. Digital phenotyping serves as the connective layer between these two systems, offering quantitative and multimodal signals that can ground LLM outputs and contextualize ontology-based reasoning. As these datasets expand, they may reduce hallucinations, strengthen ontology alignments, and improve biological validities. This two-way interaction enables closed-loop systems in which physical AI updates real-time states, and the ontology–LLM layer refines strategies and interprets emerging phenotypic patterns. Despite challenges—including incomplete ontologies and risks of hallucination—this integrated architecture represents a promising path toward biologically informed adaptive agricultural management.

Conclusions

Digital phenotyping has become a key technology linking engineering-driven physical control with life science-based genome-to-phenome research. Its ability to quantify plant responses with high spatial and temporal resolutions strengthens real-time decision systems and mechanistic trait interpretations (Mahlein 2016; Pieruschka and Schurr 2019).

The integration of physical AI with ontology–LLM frameworks offers a promising path toward adaptive, biologically grounded decision-making. Physical AI provides real-time state estimation, whereas ontology–LLM systems can interpret G × E × M interactions and generate long-term strategies (Singhal et al. 2023; Zeng et al. 2023).

Future progress depends on advances in multimodal data integration, transparent AI models, and high-quality agricultural ontologies. Digital phenotyping will continue to serve as a measurement tool and as a bridging layer unifying empirical control and biological reasoning for resilient and sustainable agro-ecosystem management.

Author contribution

Conceptualization: Kim SH, Shin YH. Methodology and supervision: Kim HS; Investigation: Kim SH, Shin YH; Resources: Park SH, Lee TS; Writing – original draft: Kim SH, Shin YH, Park SH, Lee TS, Kim HS; Writing – review and editing: Kim HS; Project administration and funding acquisition: Kim HS.

Disclosure statement

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Data availability statement

The data are available from the corresponding author upon reasonable request.

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