

Technological Application and Barriers of Modern Flower Industrialization

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Received: 27 April 2026; Accepted: 18 May 2026; Published: 3 June 2026

Abstract:

The global flower market is breaking with its trial-and-error past, stepping into a fully connected ecosystem termed Floriculture 4.0. This shift is driven by the cross-industry convergence of Artificial Intelligence (AI), the Internet of Things (IoT), and high-throughput digital phenotyping. These technologies, which were originally designed for industrial manufacturing and data science, are now fundamentally optimizing biological systems. This review provides an exhaustive analysis of the intelligent implementation and Agro-tech Operations of modern flower production and germplasm breeding. After evaluating the transition from traditional phenotypic selection to AI-driven genomic predictive modeling, we provide a rigorous, multi-dimensional comparative analysis of the world's leading production ecosystems. Specifically, we contrast the Netherlands' capital-heavy, auction-based system with China's Yunnan region, which used e-commerce to leapfrog straight into the digital age. We also look at equatorial hubs like Kenya and Ecuador, where tech adoption focuses heavily on precision cold chains, drone monitoring, and automated pest control to overcome geographical bottlenecks. Finally, using Cyber-Physical Systems (CPS) and the Technology-Organization-Environment (TOE) frameworks, we identify the socio-technical barriers to these technologies.

Keywords:

Smart Floriculture, Agro-tech Operations, Floriculture 4.0

1. Introduction

The global cut flower market is a multi-billion dollar segment in the agricultural sector. The most prominent feature of this industry is that the products are extremely perishable, the appearance quality standards are strict, and the overall market fluctuates greatly. Unlike staple grains, cut flowers are high-value light luxury agricultural products. Minor quality defects such as stem shape, petal color and leaf integrity can prevent the entire batch of products from entering the market, causing huge economic losses to practitioners [1]. The flower planting industry has always been a labor-intensive industry, which relies heavily on the experience and professional knowledge of senior growers to cope with various complex biological growth variables in the process of flower growth. At present, the flower planting industry is facing a development dilemma with multiple problems. With the continuous rise in global labor costs and the increasingly unstable climate

environment, coupled with the increasing demand of consumers for year-round supply of cut flowers, the industry urgently needs to rely on intelligent technology to complete the transformation and upgrading, so as to achieve product quality standardization, maximize yield per unit area, and effectively reduce the consumption and waste of agricultural chemicals and water resources [2].

This paradigm shift is encapsulated by the concept of Floriculture 4.0. Just as global manufacturing progressed through distinct industrial revolutions, the flower industry has evolved systematically. Floriculture 1.0 and 2.0 relied on manual cultivation and basic mechanical greenhouse structures. When the industry entered the 3.0 phase, farmers started using computers to automate part of their operations, alongside simple environmental sensors, bringing basic smart tools into day-to-day growing work. Now in the Floriculture 4.0 era, the industry deeply combines biological expertise with advanced digital technology. Powered by cloud computing and big data, modern flower farms can even run largely on their own. The dominant network technology has built a fully interconnected flower industry ecosystem. This multi-technology integration development model has broken the limitations of traditional industries' single and fragmented mechanization and automation, and constructed a new production system that can respond in real time and is driven by data as the core [3]. This industrial revolution has completely reshaped the traditional agricultural management model, making data replace traditional manpower and become the core production factor in the flower supply chain system. For industry policymakers, in-depth research into the promotion and implementation mechanism of such cross-industry technologies in different core production areas around the world is the key to balancing the global market development pattern and promoting the continuous empowerment of industrial economic growth by technological innovation.

Computer vision, machine learning, and blockchain technologies have now been applied in the floriculture industry, becoming a prime example of cross-industry technology integration [4]. Algorithms originally used for facial recognition in the security field have been adapted for early detection of gray mold in greenhouse roses. Furthermore, logistics algorithms initially used in the automotive and aviation sectors are being optimized for planning transatlantic cold chain flower transportation routes [5]. This article reviews the current application progress of these technologies, focusing on the role of artificial intelligence in front-end germplasm breeding and mid-stream production management. Simultaneously, the article analyzes the impact of different industry environments on the digitalization process, providing strategic references for industry practitioners to promote technological transformation.

2. Theoretical Framework of Technological Convergence in Agriculture

To better understand the progress of the flower production industry towards Industry 4.0, we must combine agricultural technology operation models with technology diffusion theory. This understanding is further enhanced by relying on the Cyber-Physical Systems (CPS) framework and the Technology-Organization-Environment (TOE) model. CPS combine computing power with physical equipment to achieve collaborative operation of complex tasks. In the smart scenario of flower cultivation, the physical component includes flower plants and greenhouse facilities, while the virtual component encompasses cloud-based artificial intelligence algorithms and digital twin models [6]. The entire system operates through a continuous, autonomous, closed-loop feedback mechanism: a high-density sensor

network collects massive amounts of environmental data, which is processed locally by edge computing nodes to reduce latency, then uploaded to a cloud server to run various predictive models; finally, greenhouse environmental parameters such as ventilation, lighting, and irrigation are controlled by execution equipment. This also means that traditional agricultural management models need to shift towards a system engineering mindset. Planting managers must not only pay attention to soil pH and pest and disease conditions but also strictly control technical indicators such as network latency and sensor calibration [7].

The degree of application of smart technologies varies significantly across different regions, and the TOE model can clearly explain this phenomenon. From a technical perspective, the upgrading of production techniques by flower growers primarily depends on the operational difficulty and practical effectiveness of the technology itself. Furthermore, at the organizational level, farm size, financial strength, and the digital literacy of practitioners all influence the implementation of technology. Externally, market demand, relevant policies, and supply chain support conditions drive the widespread adoption of technology [8]. The Dutch flower industry possesses mature application conditions in terms of technology, organization, and environment. However, small-scale growers in some developing economies, even those with access to cutting-edge technologies, often face limitations due to their own circumstances and external environment, making implementation difficult. This development gap illustrates that technology promotion and introduction must be tailored to local conditions [9].

3. Intelligent Germplasm Breeding: The Molecular-Digital Nexus

The foundation of the flower industry chain lies in the continuous cultivation of new flower varieties. Traditional ornamental flower breeding methods are time-consuming and inefficient; it often takes nearly ten years for a new variety to go from hybridization and selection to market launch. Today, intelligent technology is fundamentally changing this situation, and the industry is gradually shifting from experience-based, trial-and-error breeding to predictive breeding based on algorithmic models.

Phenotype identification has always been a major obstacle to the development of plant breeding. While gene sequencing technology has achieved rapid popularization and significantly reduced costs, evaluating the external traits of a large number of plants still relies on manual operation, which is time-consuming and labor-intensive. High-throughput digital phenotypic analysis technology, derived from cross-industry applications, effectively solves this problem [10]. Automated imaging equipment, combined with 3D LiDAR, multispectral cameras, and mechanical devices, can automatically collect plant morphological data; then, through convolutional neural networks analyzing the image information, it can calculate leaf area index with sub-millimeter precision, detect the degree of flower stem twisting, and assess the regularity of petal morphology. Breeders can screen tens of thousands of plants daily, while avoiding biases caused by human judgment [11].

Digital phenotypic analysis goes beyond simply observing the plant's appearance. Hyperspectral imaging and infrared thermal imaging technologies can capture subtle physiological changes within plant tissues. These technologies can identify anomalies days before visible symptoms of stress such as pests and diseases or localized water shortages appear. By combining these with machine learning models to classify early

stress signals, breeders can select disease-resistant strains early in the plant's growth [12].

The next direction for intelligent breeding is combining massive amounts of phenotypic data with genomic selection models. Breeding institutions are currently using deep learning algorithms such as random forests and support vector machines to establish correlation analyses between millions of single nucleotide polymorphism sites and various floral traits, covering core indicators such as vase life, aroma concentration, and cold tolerance [13].

Based on this predictive system, researchers can determine the commercial value of seedlings based solely on genetic information after germination, accelerating breeding and eliminating the need for costly, years-long field trials. In the Netherlands, leading breeding companies have long adopted this model of integrating genetics and digital technology as standard practice, and even use artificial intelligence to simulate the growth performance of different gene combinations under future climate change conditions. This technology not only reduces costs but also enables the targeted breeding of flower varieties adapted to different global climates [14]. Meanwhile, the protection of germplasm databases and the management of related intellectual property rights have become major challenges for agricultural technology operations. The industry urgently needs to establish a comprehensive data management system and build standardized mechanisms to ensure the orderly conduct of transnational scientific research collaborations [15].

4. Integrated Production Ecosystems: IoT, Robotics, and Digital Twin Management

In the midstream production stage of the flower industry, the application of Internet of Things (IoT) technology has long been no longer limited to basic environmental monitoring, but has now been upgraded to a fully automatic intelligent control system. This technological innovation has transformed modern commercial greenhouses into sophisticated and fully functional biological data processing centers [16,17].

Modern flower production bases have all built high-density wireless sensor networks to monitor various microclimate environmental parameters in the greenhouse in all aspects. This network can continuously monitor core production indicators such as substrate electrical conductivity (EC), pH value, photosynthetically active radiation (PAR), and vapor pressure difference (VPD) around the clock [16]. Various physical sensors transmit the collected raw data to an artificial intelligence climate control system to construct a digital twin model of the physical greenhouse. This virtual computing model can simulate the entire growth process of flower crops and accurately predict the specific impact of external weather fluctuations, indoor ventilation control, artificial lighting, and other operations on the total yield and harvest cycle of flowers [14,18].

Precise integrated water and fertilizer management is a typical application scenario of this intelligent control system. Unlike the traditional fixed-cycle extensive irrigation and fertilization model, the intelligent system can measure the actual evapotranspiration (ET) of flower crops in real time and accurately determine the current water and fertilizer needs of the plants. The system will automatically adjust the water and fertilizer supply and nutrient ratio to fully adapt to the physiological needs of different growth stages of crops. This intelligent management and control model can usually reduce water consumption and fertilizer loss by more than 30% [19,

20]. For water-scarce areas, efficient resource utilization is not only a necessary requirement for ecological protection, but also the core support for the long-term stable profitability of the flower industry [21].

The application of greenhouse robot technology has effectively solved the long-standing problem of labor shortage in global agriculture and gradually replaced manual labor in flower planting, post-harvest processing and other links [22]. The robotic arm equipped with pneumatic flexible grippers can gently complete flower seedling cultivation, transplanting and other operations, greatly reducing the mechanical damage rate of seedlings and effectively improving the survival rate of seedlings. In the harvesting stage, automated sorting production lines equipped with high-speed machine vision technology can complete the automated grading and screening of cut flowers based on multiple standards such as bud maturity, flower color uniformity, and stem length [23]. This standardized and stringent quality control system can ensure that high-quality flower products can smoothly enter the highly competitive international export supply chain.

However, the large-scale deployment of various intelligent robot systems has put forward new requirements for the quality of industry talents and has also directly exposed the significant talent skills gap in the current modern horticulture industry. The demand for industry positions is rapidly iterating, shifting from traditional low-skill manual labor to technical positions such as intelligent equipment supervision and system maintenance [24]. The role of traditional farm managers has also changed accordingly, becoming “system coordinators” who coordinate the overall situation and need to efficiently integrate the biological growth law of flowers with the operating logic of intelligent equipment. Therefore, cultivating new agricultural technology talents who are adapted to the development of smart horticulture remains the core challenge faced by university research institutions and industry cooperation organizations [25].

5. Comparative Regional Models: The Netherlands vs. Yunnan, China

The Netherlands and China’s Yunnan province stand as exemplary regions for technological advancement in the global floriculture industry, yet they follow fundamentally different development paths. A comparative analysis of the two regions reveals how institutional and geographical conditions shape the adoption and evolution of floriculture production technologies. Supported by a century-old stable land system, abundant capital and a well-established industrial cooperation network, the Netherlands has built a benchmark model centered on capital-intensive industrial automation, setting a standard for the global floriculture sector. Dutch greenhouses feature sophisticated engineering design and adopt fully closed-loop environmental control systems to maximize resource efficiency. These facilities integrate geothermal heating, AI-optimized LED lighting and carbon dioxide enrichment devices for integrated and precise operational management [18]. Furthermore, the Royal FloraHolland and its digital trading platform serve as the operational core of the Dutch floriculture industry. Leveraging big data analytics, the platform coordinates and balances global flower supply and demand in real time [15]. Thanks to a transparent and efficient algorithm-based pricing mechanism, local growers and traders have long maintained their position as a key hub for global flower logistics. Guided by in-depth collaboration between governments, enterprises and research universities, this model applies unified data standards to achieve refined management

across the entire industrial chain, ranging from breeding priorities to the allocation of transoceanic air cargo space [26].

In stark contrast, the floriculture industry in Yunnan has forged a path of leapfrog digital development. Over the past decade, Yunnan has rapidly transformed from a production region characterized by dispersed layouts and traditional cultivation methods into a massive, digitized floriculture production hub, boasting a total cultivation area exceeding 1.95 million mu (a Chinese unit of land measurement commonly equal to 666.7 square meters). Yunnan bypassed the traditional developmental stage of heavy mechanical automation, stepping directly into a phase of “smart cultivation” centered on mobile internet and the Internet of Things (IoT); by leveraging digital technologies, the industry has achieved large-scale, intelligent, and synergistic growth [16].

Unlike the Dutch model, which relies on a centralized auction and trading system, the growth momentum of Yunnan’s floriculture industry is primarily driven by its vast domestic Direct-to-Consumer (D2C) e-commerce market. The industry’s overall layout remains relatively decentralized, yet a massive volume of daily orders flows directly from rural flower fields to urban consumers, facilitated by smart social platforms, livestream e-commerce, and various specialized mobile-based channels. To adapt to this industrial landscape, the local government has invested heavily in rural digital infrastructure, establishing multiple “Digital Flower Industrial Parks” to provide small-scale growers with affordable smart sorting centers, shared digital twin systems, and supporting 5G cold-chain logistics services [25]. This unique “Enterprise + Base + Farmer” model enables digital technologies to truly benefit small and medium-sized growers and facilitates the opening of market channels; however, due to the dispersed layout of production bases, it remains difficult to achieve standardized management across the entire industrial chain, presenting persistent management challenges [27].

6. Equatorial Flower Hubs: Precision Logistics and Drone-Based Farm Management

Kenya, Colombia and Ecuador are major equatorial suppliers in the global flower trade. Blessed with favorable high-altitude climates, these regions have long supplied premium roses and seasonal blooms to European and North American markets. Constrained by insufficient capital and rugged terrain, local growers have not adopted fully controlled greenhouse systems. Instead, they apply practical technologies tailored to open-field production, to address major challenges in farm management and long-distance cross-border logistics.

Most flower farms in Kenya are located across the Rift Valley, with individual sites stretching over hundreds of hectares. Manual pest scouting is inefficient and prone to human error. For this reason, large commercial flower operations have widely adopted drones for routine field monitoring [28,29]. Ecuador and Colombia face tougher geographical limitations. Their plantations are scattered across remote mountain valleys of the Andes, far away from major consumer markets. Accordingly, local technological investment focuses heavily on logistics forecasting and reliable cold chain management.

Agricultural drones fitted with multispectral sensors fly along preset routes to conduct full-coverage grid surveys and collect data including the Normalized Difference Vegetation Index (NDVI) [30]. Powered by machine learning algorithms

running on edge computing devices, these tools quickly analyze aerial footage and spot subtle plant damage caused by spider mites, thrips, downy mildew and other pests and diseases. The system generates visual heat maps of pest infestations, helping growers apply biological agents or carry out targeted spraying [28]. This precision approach greatly cuts the use of chemical pesticides. It helps producers comply with the strict Maximum Residue Levels (MRLs) set by the European Union for imports, and fits well with local workers' proficiency in using mobile digital tools.

Cold chain stability is critical to preserving the vase life of exported roses. To tackle this issue, flower exporters in Ecuador use an integrated system combining IoT sensors and artificial intelligence, which continuously tracks temperature and humidity inside shipping containers. Machine learning models compare real-time readings with historical transport records. Once unusual temperature changes signal potential refrigeration faults, the system sends immediate alerts to logistics staff [16,17]. Farms also leverage AI to predict peak blooming periods. By analyzing local microclimate conditions in the Andes and plant phenological patterns, they can estimate harvest volumes weeks in advance. With such accurate forecasts, managers can arrange labor properly and book international air freight space ahead of time, thereby sustaining the competitiveness of the flower industry in the global market [27].

7. Management Challenges, Policy Frameworks, and Future Trajectories

The global shift toward smart floriculture brings intricate managerial and policy challenges that go far beyond simple hardware deployment, calling for coordinated strategic solutions from industry practitioners and government regulators.

Poor data interoperability remains a major obstacle to optimizing global floriculture supply chains. At present, most agricultural IoT sensors, climate controllers and sorting equipment run on closed, proprietary software protocols. Such incompatibilities result in fragmented data silos across production systems. To fully unlock the economic value of cross-industry technological integration, the floriculture industry needs unified, internationally recognized standards for data sharing. Adopting open API frameworks—similar to those widely applied in the global telecommunications industry—is essential to achieving full transparency across the entire supply chain.

As AI modelling grows increasingly dependent on large-scale datasets, clarifying data ownership has become a pressing issue. Ambiguity often arises when third-party technology providers install smart sensor networks on private farms to collect microclimate and yield information, leaving unclear who holds the rights to these data. In addition, genomic selection relies heavily on extensive plant genetic databases, which highlights the urgent need to update current breeder right protections under the UPOV Convention. Policymakers should formulate clear rules on agricultural data sovereignty, balancing open collaborative innovation with robust intellectual property protection for commercial entities [24].

The substantial upfront capital expenditure (CAPEX) required for digital twin systems, robotic sorting lines and AI software licensing creates significant entry barriers for most flower producers. Without targeted policy and industrial support, the ongoing digital transformation may further concentrate market advantages exclusively among large, capital-intensive farms. In this context, agro-tech operational strategies should embrace innovative financial models such as Agriculture-as-a-Service (AaaS).

This approach allows small and medium-sized enterprises (SMEs) to access sensor networks and cloud-based analytical tools through leasing and subscription services, instead of purchasing costly equipment outright [9,25].

8. Conclusions

The global floriculture sector is bound to embrace intelligent upgrading, driven by economic progress and technological innovation. The combination of artificial intelligence, the IoT and high-throughput phenotyping has resolved long-standing bottlenecks in this industry. With these integrated technologies, growers are able to improve flower quality, cut unit production costs and comply fully with environmental regulations at the same time.

Regions around the world have adopted vastly different approaches to this transformation. The Netherlands has set a sound example of capital-intensive industrial automation. Yunnan in China has achieved remarkable digital progress by leveraging e-commerce. Ecuador, on the other hand, has shown how targeted AI applications can address major logistics challenges. Looking ahead, fully autonomous greenhouses represent the ultimate goal for technological development in this field. Powered by continuous feedback loops, AI systems will oversee the entire crop growth cycle with little human involvement.

That said, the success of Floriculture 4.0 hinges not only on technological advances, but also on well-established agricultural technology management. All participants across the industry need to unify data standards, make technologies accessible to more practitioners and prioritize sustainable development. Learning to align intelligent systems with the natural growth patterns of crops will remain the key challenge for modern agriculture worldwide in the years to come.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this article.

Funding

This work was supported by Zhaotong University Research Start-up Fund (X212260103).

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