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Toward Viable Agricultural Supply Chains: A Digital Twin Framework with Artificial Intelligence and Immune-Inspired Control

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Abstract

This working paper proposes an integrated framework that combines digital twin technology, artificial intelligence, immune-inspired regulation, and adaptive memory to support viability-oriented decision-making in agricultural supply chains under disruption. The study is motivated by the growing interest in digital twins in both supply chain and agricultural research, alongside the limited development of frameworks capable of moving beyond monitoring and prediction toward dynamic regulation and learning. In response to this gap, the proposed architecture is structured around four tightly coupled components: a digital twin as the cyber-physical representation layer, an AI-driven state estimation and predictive modeling module, the Supply Chain Immune System (SCIS) as the regulatory layer, and Immune-Structural Adaptive Response (RAIE) as the adaptive memory layer. These components are formalized through a dynamic system in which performance evolves according to disruption effects, corrective actions, and accumulated experience. To illustrate the behavior of the framework, simulation experiments were conducted under baseline, single-disruption, and repeated-disruption scenarios. The results show that predictive capabilities improve anticipatory response, but their effect remains limited when not supported by adaptive regulation. In contrast, the integration of SCIS and RAIE leads to faster recovery, lower performance degradation, and more stable behavior under recurrent disturbances. The findings suggest that viability in agricultural supply chains depends not only on visibility and prediction, but also on the coordinated interaction of representation, control, and learning. The study contributes a conceptual and computational foundation for advancing digital twins in agriculture toward adaptive, disruption-aware, and viability-oriented systems.

Keywords: digital twin; agricultural supply chains; artificial intelligence; adaptive regulation; immune-inspired systems; viability; SCIS; RAIE

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1. Introduction

The increasing complexity of agri-food systems, combined with climate variability, resource scarcity, and the need for sustainable production, has intensified the demand for advanced decision-support and optimization frameworks in agriculture [1]. Recent technological advances associated with Agriculture 5.0—such as artificial intelligence, Internet of Things (IoT), remote sensing, and data analytics—have enabled new forms of monitoring, prediction, and control of agricultural processes [2]. Within this paradigm, digital twins (DTs) have emerged as a promising concept for integrating physical and virtual systems, enabling simulation-based decision-making and system optimization [3,4].

Digital twins are commonly defined as dynamic virtual representations of physical systems that combine real-time data, simulation models, and analytical tools to support understanding and

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decision-making across the system lifecycle [5]. Their potential lies in enabling continuous monitoring, predictive analytics, and what-if scenario evaluation, thereby improving operational efficiency and reducing uncertainty. In agriculture, DTs have been associated with applications such as crop monitoring, irrigation management, infrastructure planning, and resource optimization, often integrating heterogeneous data sources and technologies [6,7]. Despite this potential, the adoption and maturity of digital twins in agriculture remain limited. Existing studies report a relatively small number of applications, many of which are still at conceptual or prototype stages, with few fully deployed systems [4]. Furthermore, the diffusion of smart agricultural technologies—including those related to DTs—remains constrained by factors such as high implementation costs, limited data availability, technological complexity, and the structural characteristics of agricultural systems, particularly in regions dominated by small and medium-sized farms [8]. As a result, the current landscape of agricultural digital twins is characterized by fragmentation and uneven development across application domains.

Despite this potential, the adoption and maturity of digital twins in agriculture remain limited. Existing studies report a relatively small number of applications, many of which are still at conceptual or prototype stages, with few fully deployed systems [9]. Furthermore, the diffusion of smart agricultural technologies—including those related to DTs—remains constrained by factors such as high implementation costs, limited data availability, technological complexity, and the structural characteristics of agricultural systems, particularly in regions dominated by small and medium-sized farms [10]. So, the current landscape of agricultural digital twins is characterized by fragmentation and uneven development across application domains.

Beyond implementation limitations, a more fundamental gap emerges at conceptual and methodological levels [11]. Current DT applications in agriculture are predominantly designed following data-driven (datalogical) approaches, where data collection precedes problem definition. This often leads to the generation of large volumes of data without a clear linkage to decision-making needs. In contrast, decision-oriented (infological) approaches—where system objectives guide data requirements—have been proposed as more suitable for complex agricultural systems yet remain underexplored in practical DT implementations [3]. Consequently, many existing DT frameworks fail to provide coherent mechanisms for aligning system structure, data flows, and decision processes [12]. In addition, existing DT-based solutions rarely address system-level performance from a viability perspective. While metrics such as efficiency, yield, or cost reduction are frequently considered, there is limited attention to the ability of agricultural systems to maintain functionality under disruptions, adapt to changing conditions, and recover from adverse events [9]. This limitation is particularly relevant in the context of modern agri-food systems, which are increasingly exposed to compound risks, including climate shocks, supply variability, and infrastructure constraints. Even advanced approaches integrating artificial intelligence and optimization tend to operate within predefined scenarios and lack mechanisms for adaptive control, structural reconfiguration, and learning over time [7].

These limitations point to a broader issue: the absence of integrated frameworks that combine digital twin architectures with dynamic control, adaptive decision-making, and system-level performance regulation. In most existing studies, digital twins, optimization models, and intelligent algorithms are developed as loosely connected components rather than as parts of a unified system capable of continuous adaptation. As a result, the potential of digital twins to act as active control systems—rather than passive monitoring or simulation tools—remains largely unrealized in agricultural applications. In response to these gaps, this study proposes a novel framework that integrates digital twin technology with an immune-inspired adaptive control mechanism to support the design and operation of viable agro-industrial systems. The proposed approach extends conventional DT architectures by embedding feedback-driven control, adaptive response mechanisms, and memory-based learning processes, enabling the system to dynamically adjust its behavior under varying operational conditions and disruptions. By shifting the focus from static optimization and descriptive analytics toward viability-oriented system regulation, this work

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2. Literature Review

2.1. Digital Twins in Supply Chains

The concept of digital twins has gained increasing attention in supply chain management to enhance visibility, support decision-making, and improve system responsiveness under uncertainty [4]. In this context, digital twins are not limited to static representations of physical systems but are conceived as dynamic environments that integrate data streams, simulation models, and analytical tools to reflect the evolving state of the supply chain [13]. Recent developments have extended the role of digital twins toward more advanced decision-support systems [14]. In particular, the notion of digital supply chain ecosystems emphasizes the integration of heterogeneous data sources, model-based representations, and real-time analytics to enable adaptive and informed decision-making processes. Within these frameworks, digital twins are expected to provide not only descriptive insights but also predictive and prescriptive capabilities, supporting the evaluation of alternative scenarios and the anticipation of disruptions [15].

Artificial intelligence has played a central role in this evolution [16]. AI-based models are increasingly embedded within digital twin architectures to enhance state estimation, predict system behavior, and identify potential risks [5]. These capabilities are particularly relevant in environments characterized by high variability and uncertainty, where real-time decision-making requires both accurate system representation and anticipatory information [7]. Approaches combining digital twins with machine learning and deep learning techniques have demonstrated improvements in disruption detection, recovery planning, and performance prediction [9,17].

Despite these advances, literature also highlights important limitations. A significant proportion of existing implementations remain at the level of digital shadows or partial digital twins, lacking full bidirectional interaction and closed-loop control capabilities. Empirical analyses show that only a limited number of systems achieve complete integration between data, models, and decision processes, while fully autonomous and adaptive digital twin implementations remain rare [18]. As a result, many current approaches provide enhanced visibility and predictive insights but do not fully exploit the potential of digital twins as active regulatory systems[19]. These observations suggest that, although digital twins in supply chains have progressed toward more intelligent and data-driven architectures, their role as mechanisms for dynamic regulation and adaptation is still underdeveloped [5]. In particular, the integration of predictive analytics with control and learning mechanisms remains an open challenge, especially in contexts involving recurrent disruptions and evolving system conditions.

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2.2. Digital Twins in Agriculture

The application of digital twins in agriculture has emerged more recently, driven by the need to improve productivity, sustainability, and resource efficiency in complex and uncertain environments [20]. Agricultural digital twins integrate data from sensors, remote sensing technologies, and farm management systems with simulation models and analytical tools, enabling continuous monitoring and scenario-based analysis of agricultural processes [21]. In practice, most agricultural digital twin implementations focus on monitoring and predictive analytics. Applications include crop growth tracking, irrigation management, environmental condition monitoring, and quality assessment in supply chains. In these contexts, artificial intelligence is commonly employed to process heterogeneous data and generate predictive insights [4,10,20]. For example, machine learning and deep learning models have been used to estimate variables such as temperature evolution, crop yield, and product shelf life, improving decision-making in agri-food systems [12,14].

More advanced approaches have explored the integration of digital twins with optimization and learning-based decision frameworks [1]. These include simulation-based systems that support resource allocation, as well as reinforcement learning models that adapt system behavior over time to improve performance metrics such as water efficiency or crop yield [22]. Such developments indicate a transition toward more intelligent and adaptive digital twin architectures. However, the maturity of agricultural digital twins remains limited. Several studies report that many implementations are still at conceptual or prototype stages, with relatively few fully operational systems [4]. In addition, the inherent complexity of agricultural systems—characterized by biological variability, environmental uncertainty, and spatial heterogeneity proposes significant challenges for model integration and real-time control. Practical barriers such as data availability, technological costs, and limited adoption further constrain large-scale implementation [23].

Another important limitation is the predominance of descriptive and predictive functionalities over adaptive control. Many agricultural digital twins operate as monitoring or forecasting tools, providing valuable insights but lacking mechanisms to dynamically regulate system behavior. Even in cases where artificial intelligence is integrated, its role is often confined to prediction rather than embedded within a broader control architecture capable of adjusting system responses based on evolving conditions. These limitations indicate that, while digital twin applications in agriculture have advanced in terms of data integration and predictive capabilities, there remains a gap in the development of frameworks that support continuous adaptation, learning, and system-level performance regulation.

2.3. Research Gaps and Positioning of This Study

The literature reviewed highlights a consistent pattern across both supply chain and agricultural contexts, where digital twin technologies have advanced significantly in terms of data integration, simulation capabilities, and predictive analytics, yet remain limited in their ability to support adaptive and self-regulating system behavior. Current approaches provide increasingly accurate representations of system states and enable the anticipation of potential disruptions; however, the translation of these insights into structured and dynamic control actions is still not fully addressed. Artificial intelligence plays a central role in enhancing digital twin functionality, particularly in the estimation of unobservable variables and the prediction of future system conditions. Nevertheless, its integration is predominantly oriented toward improving prediction accuracy, with limited emphasis on how these predictive outputs are embedded within a broader control architecture. As a result, many existing systems operate with a clear separation between prediction and decision-making, which constrains their ability to respond coherently to complex and evolving disturbances.

Another critical limitation concerns the absence of explicit mechanisms for incorporating memory and learning into system dynamics. In most reported frameworks, responses to disruptions are based on current system conditions or predefined rules, without systematically leveraging information from past events. This restricts the system's ability to improve its response over time, particularly in environments characterized by recurrent disruptions where learning from experience

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becomes essential for maintaining performance. In addition, the lack of integration between representation, prediction, control, and learning leads to fragmented architectures in which digital twins, artificial intelligence models, and decision-support tools operate as loosely connected components. Such fragmentation limits the development of closed-loop systems capable of continuously adjusting their behavior in response to internal and external changes, thereby reducing their effectiveness in managing complex, dynamic environments.

The present study addresses these limitations by proposing an integrated framework that combines digital twin representation with an immune-inspired regulatory mechanism and adaptive memory. This approach establishes explicit links between state estimation, predictive modeling, control actions, and learning processes, enabling the system to evolve its behavior over time. By framing system performance in terms of viability, the proposed model emphasizes the capacity to maintain functional operation under disruption, offering a structured pathway toward more resilient and adaptive agricultural supply chain systems.

3. System Architecture and Dynamic Formulation

This study adopts a system-oriented methodological approach in which the digital twin is conceived as a cyber–physical decision architecture rather than as a mere virtual representation of the agricultural system. While conventional digital twins are primarily used for monitoring, simulation, and prediction, the proposed framework redefines their role by embedding them within a regulatory structure capable of interpreting system states and supporting adaptive intervention under dynamic conditions. In this context, the digital twin operates as the core representation mechanism that links data, model, and operational decision-making.

Building upon this foundation, the framework integrates an immune-inspired control system (SCIS–RAIE) that introduces capabilities for disruption detection, adaptive response, and experience-based learning. Artificial intelligence is not treated as an independent layer, but as an embedded mechanism that enables state estimation, anomaly detection, and adaptive decision-making across the system. As a result, the proposed approach conceptualizes the digital twin as part of a broader adaptive system in which representation, control, and learning are tightly coupled to sustain system viability under uncertainty.

3.1. Digital Twin as a Cyber–Physical Representation Layer

Within the proposed architecture, the digital twin is defined as the cyber–physical representation layer responsible for constructing and maintaining a consistent, dynamic mapping of the agricultural system. The digital twin operates as an integrative mechanism that connects heterogeneous data sources, modeling structures, and analytical processes into a unified representation of system states**.** This layer establishes the informational and computational basis upon which subsequent control and adaptation mechanisms are built. The digital twin continuously assimilates data from the physical system, including environmental conditions, crop status, and operational variables, transforming these inputs into a structured state representation. This representation is not static; it evolves over time as new information becomes available, enabling the system to reflect both current conditions and emerging trends. In line with cyber–physical system principles, the digital twin ensures synchronization between the physical and digital domains, allowing deviations between expected and observed performance to be identified and quantified.

Structurally, this layer comprises three tightly coupled components. First, a data assimilation component integrates real-time observations with historical information, ensuring consistency and completeness of the input space. Second, a model backbone combines mechanistic relationships with data-driven models to capture the behavior of the agricultural system under varying conditions. Third, a simulation and analysis component enables the exploration of system trajectories, supporting both predictive assessment and scenario evaluation. Together, these components define a representation layer that is both descriptive and anticipatory, providing the necessary inputs for higher-level decision processes.

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From a functional perspective, the digital twin performs three core tasks. It estimates the current state of the system, predicts its short-term evolution, and generates performance indicators that reflect operational conditions. These outputs include, among others, measures of system performance, imbalance between supply and demand, and indicators of degradation or stress. Importantly, the digital twin does not directly execute control actions; instead, it provides the structured information required by the SCIS–RAIE layer to detect perturbations and determine appropriate responses.

This conceptualization is consistent with recent developments in digital twin research, where the twin is understood as part of a broader digital ecosystem integrating data, models, and analytics into decision-support processes (see Figure 1). However, in contrast to approaches where the digital twin remains primarily predictive, the present framework positions it as a representation layer embedded within a closed-loop adaptive system. As illustrated in Figure 1, the digital twin feeds the control layer with continuous state updates, enabling the transition from passive observation to active system regulation.

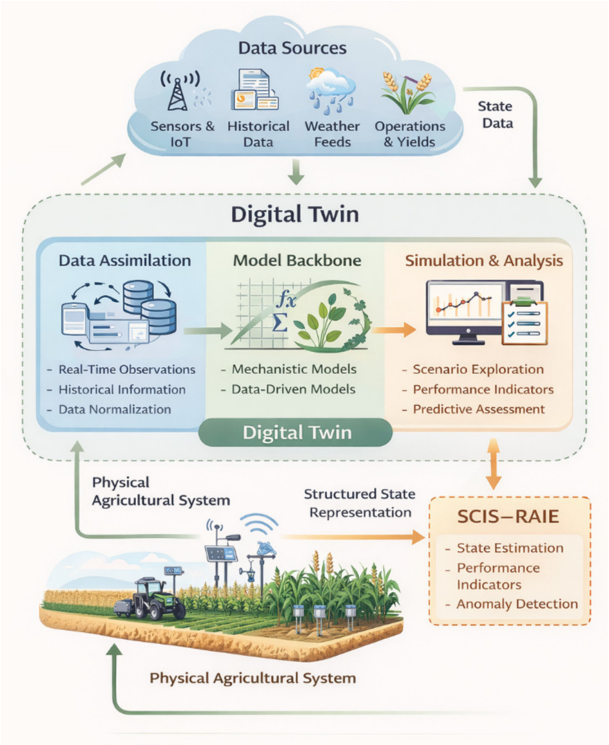

Figure 1. Digital Twin as a Cyber–Physical Representation Layer.

By isolating the digital twin as a dedicated representation layer, the architecture preserves conceptual clarity while allowing for modular integration with control and learning mechanisms. This separation is critical for enabling the subsequent incorporation of immune-inspired responses, ensuring that the processes of observation, decision, and adaptation remain functionally distinct yet dynamically coupled.

3.2. AI-Driven State Estimation and Predictive Modeling

The effectiveness of the proposed architecture depends on the ability to construct an accurate and dynamically updated representation of system conditions. In agricultural systems, a significant portion of relevant variables cannot be directly observed or measured in real time. This limitation introduces uncertainty into the digital twin representation, particularly when system behavior is influenced by nonlinear interactions, environmental variability, and delayed effects. To address this

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challenge, the framework incorporates an artificial intelligence–driven component dedicated to state estimation and predictive modeling. This component operates as a data-driven engine that complements the mechanistic structure of the digital twin. Its primary function is to infer latent system variables from heterogeneous data sources, including historical records, environmental inputs, and operational observations. By learning patterns and dependencies within these data streams, the AI module enhances the descriptive fidelity of the digital twin, allowing it to represent not only observable conditions but also hidden dynamics that influence system performance.

The AI component supports both state estimation and short-term prediction by reconstructing variables that are not directly observable, such as future yield conditions, disruption intensity, or system stress levels. By capturing temporal dependencies within the data, it enables the anticipation of system deviations before they fully materialize. This capability is particularly valuable in agricultural settings, where uncertainty and delayed effects reduce the effectiveness of purely reactive decision-making. The integration between the digital twin and the AI component is continuous and bidirectional. The digital twin supplies structured data and contextual information that serve as inputs for the learning process, while the AI module updates the state representation by refining predictions and correcting deviations between expected and observed behavior. This interaction results in a hybrid modeling environment in which mechanistic and data-driven approaches coexist, improving robustness under uncertain and evolving conditions.

The role of artificial intelligence within architecture extends beyond prediction. By providing refined state estimates, it directly influences the operation of the regulatory layer (SCIS), which relies on these inputs to detect anomalies and activate adaptive responses. In this sense, the AI component acts as a critical interface between system observation and decision-making, enabling the transition from data acquisition to be informed control actions.

The AI component is implemented using deep learning architectures designed to capture temporal dependencies and nonlinear dynamics within the agricultural system. Recurrent neural networks, such as Long Short-Term Memory (LSTM) models, are employed to learn the evolution of system states over time. These models process sequential data streams derived from historical observations, environmental variables, and operational indicators, enabling the estimation of latent variables and the prediction of future system conditions.

Through this approach, the AI module constructs a dynamic mapping between observed inputs and system responses, allowing the digital twin to extend beyond static representation. The learned temporal patterns enable the identification of early signals of disruption, as well as the anticipation of system degradation or recovery trajectories. This predictive capability is continuously updated as new data becomes available, ensuring that the system representation remains consistent with evolving conditions (Figure 2).

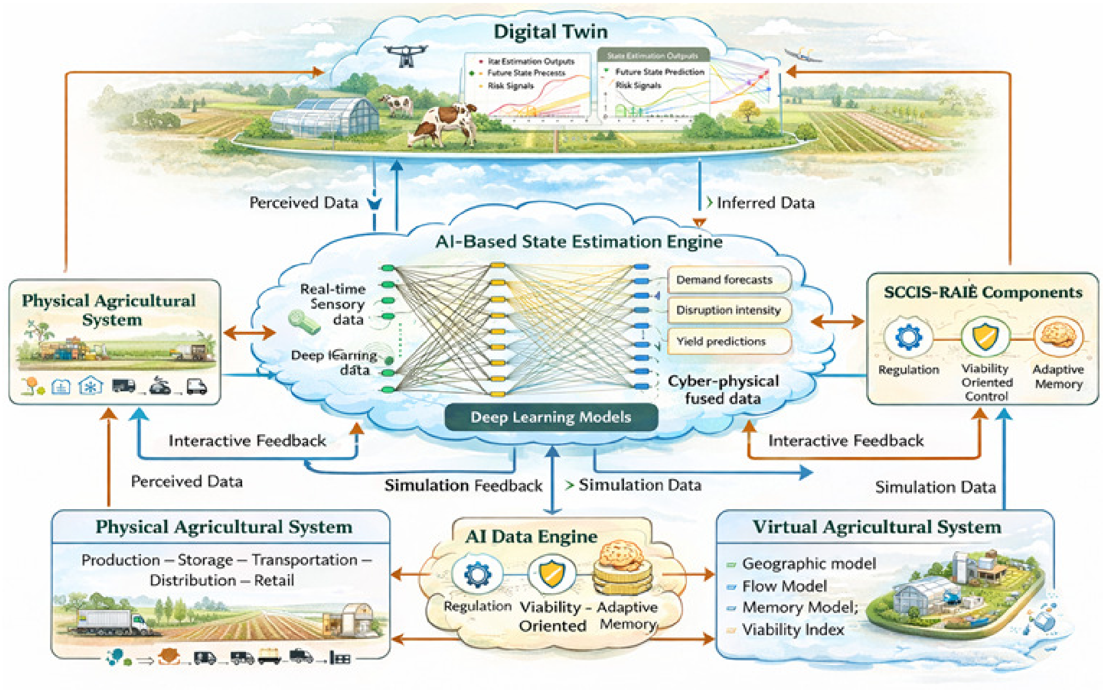

Figure 2. AI-Driven State Estimation in SCIS RAIE Digital Twin framework.

3.3. SCIS as the Regulatory Layer

The Supply Chain Immune System (SCIS) is defined as the regulatory layer that governs the behavior of the agricultural system based on the state representation provided by the digital twin. This layer translates the information generated by the representation mechanism into operational decisions, enabling the system to respond to perturbations and maintain functional stability. In this sense, SCIS operates as the decision-making core of architecture, bridging the gap between system observation and system intervention. The SCIS layer is structured around three interrelated functions: detection, response, and regulation. The detection function is responsible for identifying deviations between expected and observed system behavior, based on the continuous monitoring of state variables and performance indicators. These deviations are interpreted as signals of potential disruption, activating the regulatory process. This mechanism is supported by data-driven models that allow the identification of anomalies, trends, and emerging risks within the system.

The regulatory capability of the proposed system is embodied in the Supply Chain Immune System (SCIS), which introduces an operational logic centered on detection, intervention, and stabilization. Its function emerges once the system state has been constructed by the digital twin, shifting the role of the architecture from representation to action. At this stage, the system no longer focuses on describing conditions but on actively managing their evolution under perturbation. Regulatory behavior is initiated through the continuous evaluation of system deviations. Instead of relying on predefined disruption scenarios, the SCIS interprets variations in performance indicators as signals of instability. These signals trigger a response process that is inherently hierarchical. Immediate reactions are deployed to contain localized effects, while more elaborated responses adjust system configuration through changes in allocation, scheduling, or operational parameters. This dual mechanism reflects a transition from reactive containment to adaptive restructuring, allowing the system to operate under varying levels of disturbance.

Beyond response activation, SCIS introduces a stabilizing logic that governs how interventions are applied over time. Actions are not executed in isolation; they are modulated to avoid oscillatory or disproportionate behavior that could compromise system performance. This regulatory function ensures that corrective measures remain aligned with system constraints and long-term operational balance. In this sense, regulation is not equivalent to response, but to the controlled orchestration of responses within acceptable boundaries. SCIS can be interpreted as a dynamic policy that continuously maps system conditions into decision spaces. This mapping is neither fixed nor purely rule-based, as it evolves through interaction with both the digital twin and the adaptive memory component. As illustrated in Figure 3, the regulatory layer operates within a closed-loop structure in which state observation, deviation assessment, and decision execution are recursively linked. Through this mechanism, the system acquires the ability to operate under uncertainty without relying on externally defined control strategies.

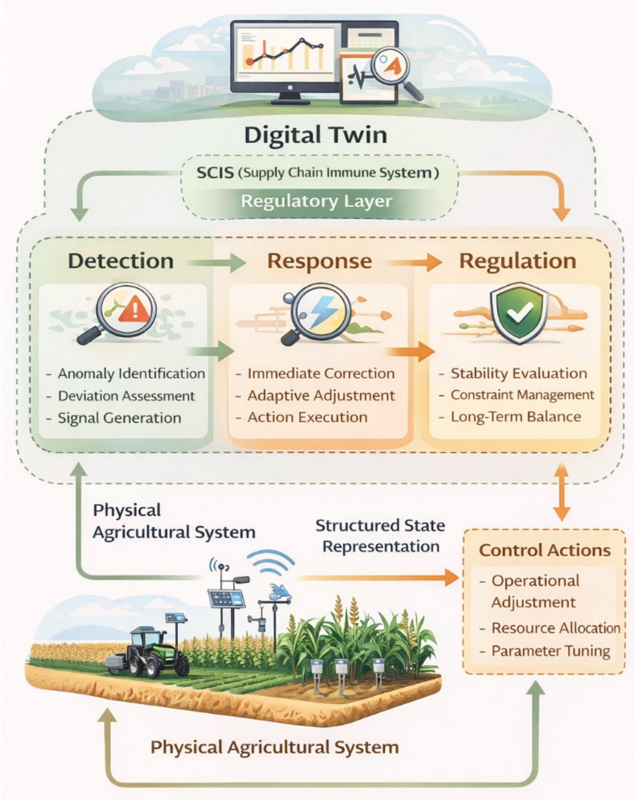

Figure 3. SCIS as the Regulatory Layer.

By embedding this regulatory layer into the architecture, the framework enables a shift toward endogenous system governance. The agricultural system is no longer dependent on ex-post adjustments or static planning assumptions but instead operates through continuous adaptation driven by internal control mechanisms. This capability is particularly relevant in environments characterized by variability and recurrent disruptions, where maintaining functional stability becomes a prerequisite for long-term viability.

3.4. RAIE as the Adaptive Memory Layer

A distinctive element of the proposed framework is the incorporation of an adaptive memory layer, formalized through the Immune-Structural Adaptive Response (RAIE). This component introduces a persistent representation of past system states, disruptions, and response outcomes, enabling the system to retain and reuse experiential knowledge over time. In contrast to conventional data storage or offline learning approaches, RAIE is embedded within the operational dynamics of the system, allowing memory to directly influence ongoing decision processes.

Functionally, the RAIE layer captures the interaction between disturbances, control actions, and system trajectories, transforming these interactions into structured knowledge. This process involves recording the conditions under which disruptions occur, the responses that are activated, and the resulting system performance. Through iterative updates, the memory evolves into a repository of

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system behavior patterns, which can be accessed to adjust future responses. In this way, the system does not rely solely on real-time information, but leverages accumulated experience to refine its reactions, reduce response latency, and improve decision consistency across similar events.

The relevance of this layer becomes evident in environments characterized by recurrent variability and incomplete information, such as agricultural systems. Without a mechanism for retaining and exploiting experience, each perturbation would be treated as an isolated event, forcing the system to react without contextual awareness. The RAIE layer addresses this limitation by introducing continuity across decision cycles, enabling the system to recognize patterns, anticipate potential impacts, and adapt its control strategies accordingly. Figure 4 shows the memory layer interacts with both the digital twin and the SCIS regulatory mechanisms, forming a feedback structure in which past system behavior informs future adaptation.

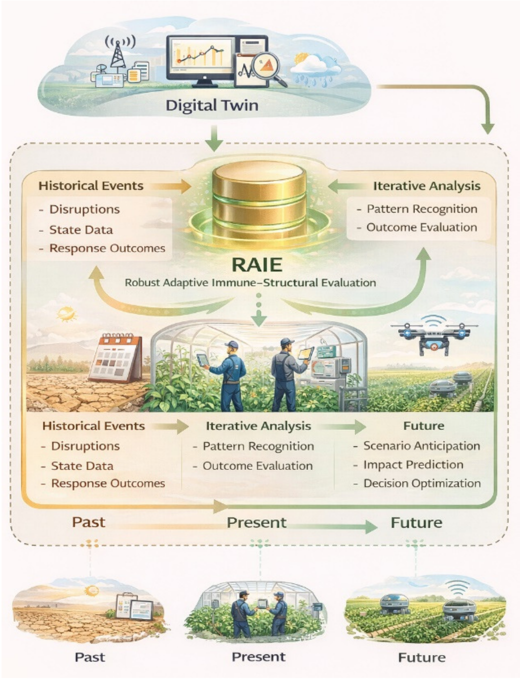

Figure 4. RAIE as the Adaptive Memory Layer.

At the system level, RAIE extends the role of the digital twin beyond representation and regulation by embedding a temporal dimension that allows the architecture to evolve. This capability enables a transition from reactive adaptation toward informed and progressively refined responses, contributing to the preservation of system viability under repeated or uncertain disruptions.

The adaptive memory layer is not limited to storing past system states but is constructed through learning mechanisms derived from the AI component. The deep learning models embedded in the architecture capture temporal patterns associated with disruptions and system responses, enabling the identification of recurrent behaviors. These learned representations are incorporated into the RAIE layer, allowing the system to recognize similar conditions and adjust its response strategies accordingly.

In this context, memory is not treated as a static repository, but as an evolving structure shaped by data-driven learning. The interaction between AI-based temporal modeling and memory construction enables the system to reduce response uncertainty, improve reaction time, and enhance consistency across repeated disruptions. This integration transforms memory into an active component of system regulation, directly influencing the decisions generated by the SCIS layer.

3.5. Viability-Oriented Coupling of Representation, Control, and Learning

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The proposed framework reaches its full operational meaning through the coupling of representation, control, and learning into a unified viability-oriented system. Rather than operating as independent components, the digital twin, SCIS, and RAIE interact continuously, forming a tightly integrated structure in which system observation, intervention, and adaptation co-evolve over time. This coupling defines the transition from modular architecture to a coordinated system capable of sustaining functionality under dynamic conditions.

At the core of this integration lies the circulation of information across layers. The digital twin provides a structured and continuously updated representation of system states, which is interpreted by the regulatory mechanisms of SCIS to generate adaptive responses. These responses, once executed, alter the trajectory of the physical system, producing new states that are again captured by the digital twin. The RAIE layer closes this loop by embedding past system behavior into the decision process, allowing previously observed patterns to influence future responses. Through this recursive interaction, the system evolves from reactive adjustment toward informed adaptation.

3.6. Dynamic System Formulation and AI-Integrated Operational Logic

The behavior of the proposed architecture is formalized as a dynamic system in which representation, estimation, control, and memory evolve jointly over time. The system state is characterized through an operational performance variable $P(t) \in [0,1]$, which captures the aggregate condition of the agricultural supply chain at time t. This variable reflects the combined effect of production, logistics, and demand fulfillment processes, and evolves under the influence of disruptions and regulatory actions. The evolution of system performance is described as:

$$P(t+1) = P(t) + R(t) - D(t) + \varepsilon(t)$$

where $R(t)$ represents the effect of corrective actions, $D(t)$ denotes disruption-induced degradation, and $\varepsilon(t) \sim \mathcal{N}(0,\sigma^2)$ captures stochastic variability. This formulation establishes the dynamic foundation of the system, linking physical evolution with decision-driven intervention.

A key feature of the proposed framework is the explicit incorporation of an AI-driven state estimation mechanism within the digital twin. In practical settings, system performance cannot be fully observed due to delays, noise, and incomplete information. To address this limitation, a data-driven model is used to infer latent system conditions based on historical and real-time data streams:

$$\hat{P}(t) = \mathcal{F}_{AI}(X_{1:t})$$

where $\hat{P}(t)$ denotes the estimated system state and $\mathcal{F}_{AI}(\cdot)$ represents a deep learning model, such as a Long Short-Term Memory (LSTM) network, trained to capture temporal dependencies in the data. This estimated state complements the observed performance by providing a forward-looking representation of system behavior.

The deviation signal that activates regulatory actions is defined by combining observed and predicted performance:

$$e(t) = w_1(1 - P(t)) + w_2(1 - \hat{P}(t+1))$$

where w_1 and w_2 are weighting parameters that balance reactive and anticipatory components. This formulation allows the system to respond not only to current performance deterioration but also to expected future degradation, embedding predictive awareness into the control process.

Regulatory intervention is governed by a proportional policy that scales corrective actions according to the magnitude of the deviation:

$$u(t) = k \cdot e(t)$$

where k is a sensitivity parameter controlling the intensity of the response. This control input determines how strongly the system reacts to deviations, enabling calibrated intervention under varying conditions.

The adaptive memory mechanism is represented as a dynamic state that accumulates information about past deviations:

$$M(t+1) = \alpha M(t) + (1 - \alpha)e(t)$$

where $\alpha \in [0,1]$ is a retention parameter governing the persistence of memory. This formulation captures the system's exposure to disruptions and encodes historical experience into a compact state variable.

Memory directly influences the effectiveness of corrective actions through the restoration term:

$$R(t) = (k_r + \beta M(t))e(t)$$

where k_r is a baseline recovery parameter and β controls the contribution of accumulated experience. As memory increases, the system becomes more effective in responding to disruptions, reflecting learning-driven improvement.

The disruption term is defined as:

$$D(t) = \gamma \cdot \text{Shock}(t) \cdot (1 + \phi(1 - e^{-M(t)}))$$

which captures both exogenous disturbances and their interaction with system conditions. This formulation allows repeated disruptions to be mitigated through accumulated experience, linking memory with resilience.

These equations define a closed-loop adaptive system in which the digital twin provides state representation, the AI component refines this representation through predictive estimation, the SCIS layer generates control actions, and the RAIE mechanism accumulates experience over time. The integration of observed and estimated states within the deviation signal constitutes the key mechanism through which artificial intelligence influences system behavior, enabling anticipatory regulation and enhancing the system's ability to maintain viability under uncertainty.

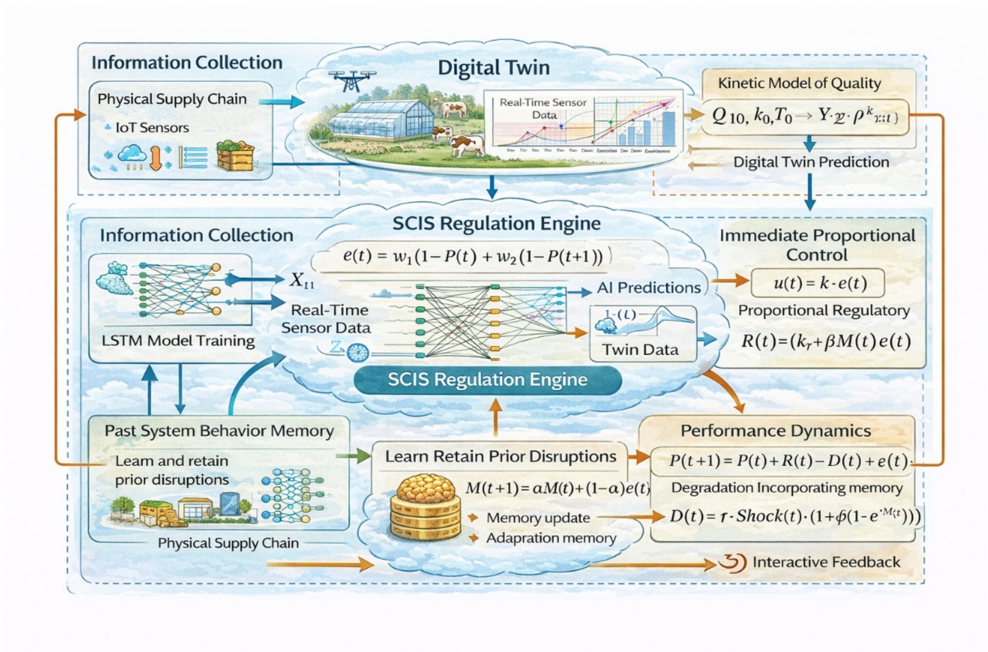

Figure 5. AI-driven digital twin and SCIS–RAIE operational flow for adaptive supply chain regulation. The figure illustrates the integrated information and control flow underlying the proposed framework. Data collected from the physical agricultural supply chain, including IoT sensor measurements and operational attributes, are processed within the digital twin and the AI-based data engine. The deep learning component (e.g., LSTM) generates state estimates and short-term predictions that complement observed system performance.

The information flow depicted in Fig. X directly corresponds to the mathematical structure of the proposed system. Data collected from the physical agricultural supply chain, including sensor measurements and operational attributes, are processed by the AI-based data engine to generate an estimated system state $\hat{P}(t)$. This estimation complements the observed performance $P(t)$, forming a combined deviation signal $e(t)$ that integrates both reactive and anticipatory information. The deviation signal serves as the primary input to the SCIS regulatory mechanism, which determines the intensity of corrective actions through a proportional control policy $u(t)$. These actions are further modulated by the adaptive memory state $M(t)$, which accumulates past system experience and enhances recovery effectiveness over time. As a result, the restoration term $R(t)$ becomes a function of both current deviations and learned system behavior.

The evolution of system performance is governed by the dynamic balance between corrective actions and disruption effects, as described by $P(t+1) = P(t) + R(t) - D(t) + \varepsilon(t)$. The disruption term $D(t)$ incorporates both external shocks and memory-dependent mitigation, reflecting the system's increasing resilience under repeated disturbances. This integrated flow demonstrates how data acquisition, AI-based estimation, immune-inspired regulation, and adaptive memory jointly define a closed-loop dynamic system capable of maintaining viability under uncertainty.

4. Illustrative System Behavior Under Disruption Scenarios

4.1. System Configuration

To illustrate the operational behavior of the proposed architecture, a simplified agricultural supply chain is considered. The system represents a first-mile production and distribution network for fresh produce (e.g., peas), where performance evolves over time under the influence of disruptions and adaptive interventions. The objective of this configuration is not to replicate a specific real-world system, but to provide a coherent environment in which the interaction between representation, prediction, regulation, and memory can be observed.

The supply chain is modeled as an aggregated system whose state is described by a normalized performance variable $P(t) \in [0,1]$. This variable captures the overall operational condition of the system, integrating effects related to production consistency, logistics efficiency, and demand fulfillment. Values close to one indicate stable operation, while lower values reflect degradation due to disruptions or ineffective responses. System evolution is driven by the dynamic relationship defined in Section 3, where performance changes because of corrective actions $R(t)$, disruption effects $D(t)$, and stochastic variability $\varepsilon(t)$. Disruptions are introduced as exogenous shocks that affect system performance over time, representing events such as supply shortages, transportation delays, or environmental variability.

The digital twin continuously updates the system state using observed data and AI-based estimation. The observed component $P(t)$ reflects the current operational condition, while the estimated state $\hat{P}(t)$, generated through the AI module, provides a forward-looking approximation of system evolution. Together, these variables define the deviation signal $e(t)$, which drives the regulatory response. The SCIS layer determines corrective actions through a proportional control mechanism, while the RAIE component accumulates past deviations in the memory state $M(t)$. This memory influences future responses by modifying the effectiveness of corrective actions, allowing the system to adapt progressively under repeated disturbances.

The simulation is conducted over a discrete time horizon, where each time step represents an operational period (e.g., day or week). Initial conditions are defined such that the system starts from a stable state $P(0) \approx 1$, with no prior memory $M(0) = 0$. Disruptions are then introduced to observe how the system deviates, reacts, and stabilizes under different configurations of the framework. This configuration establishes a controlled environment in which the contribution of each component—AI-based estimation, immune-inspired regulation, and adaptive memory—can be isolated and analyzed in terms of their impact on system dynamics and viability.

To examine the behavior of the proposed system, a set of controlled disruption scenarios is defined. These scenarios are designed to progressively stress the system and reveal how representation, prediction, regulation, and memory interact under different operational conditions. The intention is not to exhaustively explore all possible disturbances, but to capture representative patterns that allow observing the system's adaptive dynamics.

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A baseline scenario is first established, in which the system operates without disruptions. In this case, the performance variable $P(t)$remains close to its nominal level, and the deviation signal $e(t)$is negligible. This scenario serves as a reference to characterize stable system behavior and to verify that the control and memory mechanisms remain inactive in the absence of perturbations.

A second scenario introduces a single disruption event affecting system performance over a limited time interval. This disruption is modeled through the term $D(t)$, which induces a temporary degradation in $P(t)$. The objective of this scenario is to observe how the SCIS regulatory mechanism reacts to an isolated disturbance, as well as to evaluate the role of AI-based estimation in anticipating the impact of the disruption through $\hat{P}(t)$. The system response is expected to exhibit a decline followed by a recovery phase driven by corrective actions $R(t)$.

A third scenario considers repeated disruptions occurring over time, representing more realistic conditions in agricultural systems where disturbances are not isolated but recurrent. In this setting, the memory variable $M(t)$becomes critical, as it accumulates information about previous deviations and influences subsequent responses. This scenario allows analyzing whether the system improves its response over time, reducing recovery delays and stabilizing performance more effectively as experience is accumulated.

Across all scenarios, disruptions are implemented as time-dependent shocks affecting the degradation term $D(t)$. The intensity and timing of these shocks are predefined to ensure comparability across configurations. The same set of scenarios is applied under different system configurations, enabling the evaluation of the isolated and combined effects of the AI estimation and memory mechanisms.

This structured set of scenarios provides a consistent basis for analyzing system behavior, allowing the identification of differences between reactive and adaptive responses, as well as the contribution of predictive and memory-driven mechanisms to the preservation of system viability.

The system's behavior is simulated over a discrete time horizon by iteratively updating the key state variables defined in Section 3. The simulation focuses on the interaction between system performance $P(t)$, deviation signal $e(t)$, control action $u(t)$, and adaptive memory $M(t)$, which jointly determine the system trajectory under different disruption scenarios.

The initial conditions correspond to a stable operating state, with $P(0) \approx 1$and $M(0) = 0$. At each step, the deviation signal is computed based on both observed performance and AI-based state estimation, allowing the system to incorporate anticipatory information into its response. This signal drives the regulatory mechanism, which determines the magnitude of corrective actions. The memory variable evolves as a function of past deviations, influencing the effectiveness of subsequent responses. As a result, the system exhibits a progressive adaptation behavior, where repeated exposure to disruptions modifies the response dynamics over time. Disruption effects are introduced exogenously through predefined scenario profiles, affecting system performance according to their intensity and duration. The simulation captures how these disturbances interact with the regulatory and memory mechanisms, shaping the overall system response.

The iterative execution of this process allows analyzing how performance trajectories evolve under different configurations of the framework, particularly in terms of recovery speed, stability, and sensitivity to repeated disruptions. Special attention is given to the role of AI-based estimation in enabling anticipatory responses, as well as to the contribution of memory in enhancing system adaptation.

5. Results

5.1. Baseline System Behavior and Stability

The baseline scenario establishes the reference behavior of the system under nominal operating conditions. As shown in Figure 6a, system performance remains close to its desired level across all configurations, with P(t) fluctuating within a narrow band around unity. These small variations are associated with stochastic noise and do not reflect structural instability.

No significant differences are observed between the reactive baseline and the DT+AI configuration, indicating that the incorporation of predictive capabilities does not induce unnecessary control actions when the system operates within its normal regime. This is further confirmed in Figure 6c, where control intensity remains close to zero throughout the time horizon.

The SCIS–RAIE configuration exhibits a similar performance trajectory, preserving stability while introducing a latent adaptive mechanism. As illustrated in Figure 6b, the memory state M(t) shows a marginal activation, capturing minor operational variability without triggering corrective interventions. This behavior reflects the ability of the system to accumulate information without compromising stability.

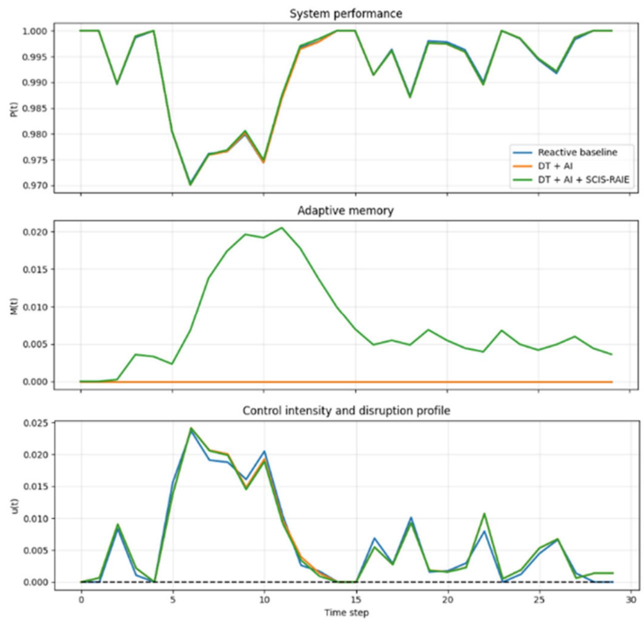

Figure 6. Baseline system behavior across configurations.

Table 1 summarizes the main performance indicators for this scenario. All configurations achieve comparable average and final performance levels, with negligible differences in minimum performance values. These results confirm that the proposed framework does not introduce artificial instability or excessive responsiveness under normal conditions, preserving operational efficiency while maintaining readiness for potential disruptions.

Table 1. Performance summary under baseline conditions.

Configuration	Avg P(t)	Min P(t)	Final P(t)	Peak M(t)
Reactive baseline	0.992	0.970	1.000	0.000
DT + AI	0.992	0.970	1.000	0.000
DT + AI + SCIS–RAIE	0.992	0.970	1.000	0.020

5.2. System Response Under a Single Disruption

The single disruption scenario introduces a temporary shock that affects system performance over a limited time interval. The impact of this disturbance and the subsequent recovery process are illustrated in Figure 7a. All configurations exhibit a sharp decline in P(t) immediately after the disruption, confirming that the shock effectively perturbs system stability.

Clear differences emerge in both the depth of the performance drop and the recovery trajectory. The reactive baseline shows the most pronounced degradation, reaching the lowest performance level among all configurations. The DT+AI configuration slightly mitigates this effect, indicating that anticipatory information contributes to reducing the severity of the disruption. However, the improvement remains limited, as the system still relies on reactive correction mechanisms.

The SCIS–RAIE configuration exhibits a markedly different behavior. As shown in Figure 7a, the minimum performance level is higher compared to the other configurations, and the recovery process is significantly faster. This improvement is associated with the activation of adaptive memory, illustrated in Figure 7b. The memory state M(t) increases during the disruption and gradually decays afterward, capturing the system's exposure to the disturbance without remaining permanently active.

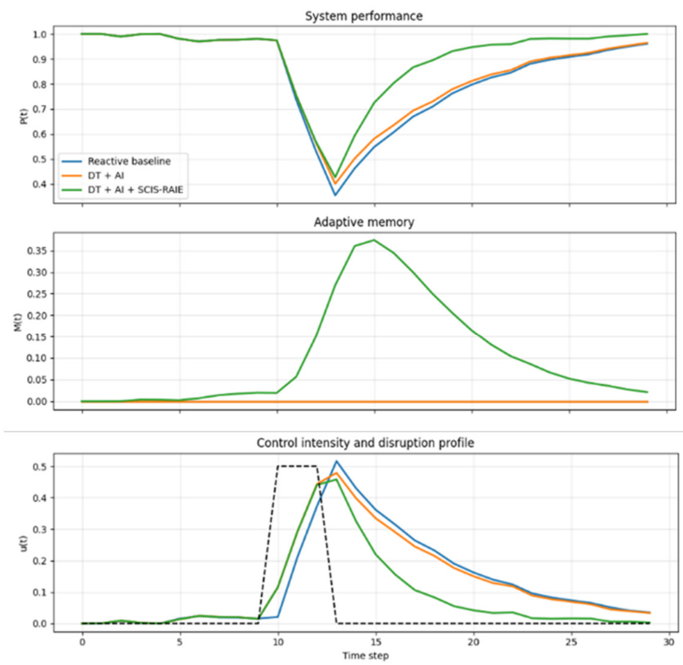

Figure 7. System response under a single disruption.

The effect of memory is also reflected in control dynamics. Figure 7c shows that the SCIS–RAIE configuration adjusts control intensity more effectively over time, avoiding excessive corrections while maintaining a stronger recovery response. In contrast, the reactive baseline exhibits a delayed and less efficient adjustment, while the DT+AI configuration provides only marginal improvements.

Table 2 summarizes the performance indicators for this scenario. The SCIS–RAIE system achieves the highest average performance and the best final recovery level, reaching P(t) ≈ 1 by the end of the simulation horizon. These results indicate that the integration of adaptive memory enhances both resilience and recovery effectiveness under isolated disruptions. The observed behavior is consistent with the proposed dynamic formulation. The restoration mechanism is reinforced by the memory-dependent component, enabling the system to recover more efficiently after the disturbance. This confirms that the framework not only reacts to disruptions but also adjusts its response based on accumulated experience, even in scenarios involving a single perturbation.

Table 2. Performance summary under single disruption.

Configuration	Avg P(t)	Min P(t)	Final P(t)	Peak M(t)
Reactive baseline	0.838	0.355	0.961	0.000
DT + AI	0.850	0.401	0.965	0.000
DT + AI + SCIS–RAIE	0.906	0.427	1.000	0.374

5.3. System Behavior Under Repeated Disruptions

The repeated disruption scenario provides a more demanding setting in which the system is exposed to successive shocks over time. The resulting performance trajectories, shown in Figure 8a, reveal substantial differences between configurations, highlighting the role of adaptive mechanisms in sustaining system functionality.

The reactive baseline exhibits cumulative degradation, with each disruption causing a deeper decline in P(t) and an incomplete recovery before the next disturbance occurs. This leads to a progressive deterioration of system performance, eventually stabilizing at a significantly lower level. Such behavior reflects the absence of adaptive mechanisms, where responses remain purely reactive and fail to account for prior disruption exposure.

The DT+AI configuration introduces moderate improvements by incorporating anticipatory information into the response process. As observed in Figure 8a, the depth of performance drops is slightly reduced, and recovery trajectories show marginal acceleration. However, these improvements remain limited under repeated disruptions, as the system lacks a mechanism to adapt its response based on accumulated experience.

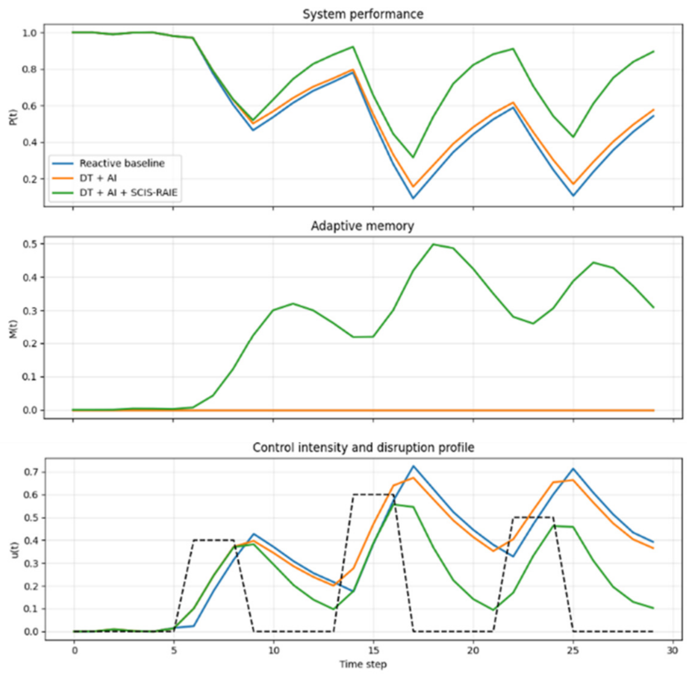

Figure 8. Performance summary under repeated disruptions.

In contrast, the SCIS–RAIE configuration maintains performance within a substantially higher range throughout the simulation horizon. Although disruptions still induce noticeable declines, the system demonstrates faster recovery and reduced degradation over successive cycles. This behavior is directly linked to the evolution of the memory state M(t), illustrated in Figure 8b. Memory

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accumulates as disruptions occur, reaching higher levels than in the single disruption scenario, and remains active across successive events.

The presence of memory significantly alters the control dynamics. Figure 8c shows that the SCIS–RAIE configuration sustains a more consistent and effective control response, adjusting intervention intensity in accordance with both current deviations and past system behavior. This results in a more balanced regulation process, avoiding both underreaction and excessive control effort.

Table 3 summarizes the performance indicators for this scenario. The SCIS–RAIE system achieves a substantially higher average performance and a significantly improved minimum performance level compared to the other configurations. Most notably, the final performance remains close to its nominal value, indicating that the system retains its operational functionality despite repeated disturbances. These results align with the concept of viability, where system performance is not expected to remain optimal at all times but must be maintained within acceptable bounds under dynamic and uncertain conditions. The incorporation of adaptive memory enables the system to transition from reactive behavior to experience-based adaptation, improving its capacity to withstand and recover from recurrent disruptions.

Table 3. Performance summary under repeated disruptions.

Configuration	Avg P(t)	Min P(t)	Final P(t)	Peak M(t)
Reactive baseline	0.584	0.094	0.543	0.000
DT + AI	0.613	0.158	0.577	0.000
DT + AI + SCIS–RAIE	0.765	0.318	0.895	0.498

The observed dynamics are consistent with the proposed formulation, where memory reinforces the restoration mechanism and modulates the impact of disruptions. As disruption exposure increases, the system exhibits progressively stronger recovery responses and improved stability. This behavior indicates that viability emerges from the interaction between regulation, learning, and system dynamics, where adaptive mechanisms enable the system to sustain performance under recurrent disturbances.

6. Discussion

The results highlight a consistent pattern across scenarios, where system performance is determined not only by the magnitude of disruptions but by the structure of the response mechanisms embedded in the system. Under stable conditions, all configurations exhibit similar behavior, confirming that the proposed framework does not introduce unnecessary interventions. This characteristic is essential, as it ensures that adaptive mechanisms remain dormant when not required, preserving operational efficiency. Differences become evident once disruptions are introduced. In the case of a single disturbance, the inclusion of predictive capabilities through the digital twin and AI improves the system's ability to anticipate performance degradation. However, this anticipatory capacity alone is insufficient to significantly alter recovery dynamics. The results indicate that prediction enhances responsiveness but does not fundamentally change the system's ability to recover from disturbances.

The presence of adaptive memory introduces a structural shift in system behavior. The SCIS–RAIE configuration demonstrates that memory accumulation modifies the effectiveness of corrective actions, allowing the system to respond more efficiently over time. With repeated disruptions, systems lacking memory show ongoing deterioration. In contrast, the memory-enabled system maintains performance within acceptable bounds, even when exposed to successive disturbances. These findings are aligned with the viability perspective, in which system performance is evaluated in terms of its ability to remain functional under changing and uncertain conditions. The results show that maintaining viability requires more than reactive control or predictive estimation. It depends on

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the integration of regulation and learning mechanisms that adapt the system's response based on prior experience.

Integration of AI within the digital twin extends its role beyond representation and short-term prediction. The AI component contributes to shaping the deviation signal that drives regulatory actions, embedding anticipatory information directly into the control process. This integration allows the system to respond to expected conditions in addition to observed states, improving responsiveness under dynamic environments. The incorporation of RAIE introduces a temporal dimension into system adaptation. Memory accumulation enables the system to retain information about disruption patterns, which subsequently influences future responses. This mechanism supports an evolving form of adaptive regulation, improving both recovery speed and stability under repeated stress conditions.

Results indicate that viability arises through the coordinated interaction of representation, prediction, regulation, and memory. Systems that rely exclusively on reactive or predictive mechanisms exhibit limited capacity to sustain performance under recurrent disruptions. In contrast, configurations that incorporate adaptive memory demonstrate improved robustness and more stable recovery trajectories, highlighting the role of learning-driven adaptation in maintaining system functionality under uncertainty.

7. Conclusions

This working paper presented an integrated framework that combines digital twin representation, AI-based state estimation, immune-inspired regulation, and adaptive memory to support viability in agricultural supply chains under disruption. The proposed approach formalizes the interaction between these components through a dynamic system in which performance evolves as a function of corrective actions, disruption effects, and accumulated experience. Results demonstrate that predictive capabilities alone are not sufficient to sustain system performance under repeated disruptions. While the incorporation of AI improves anticipatory response, its impact remains limited when not supported by adaptive regulatory mechanisms. The introduction of memory through the RAIE component significantly enhances system behavior, enabling more effective recovery and reducing performance degradation over successive disruption events.

The analysis highlights that viability is not achieved through static optimization or isolated predictive improvements, but through the coordinated interaction of monitoring, control, and learning mechanisms. In this context, the SCIS–RAIE framework enables the system to adjust its response dynamically, using both current and historical information to maintain functionality under uncertain conditions.

This work contributes to the literature by extending viability-oriented supply chain modeling with an explicit representation of adaptive memory and its interaction with AI-driven estimation and regulatory control. The proposed formulation provides a structured way to capture how systems evolve under disruption, offering insights into the mechanisms that support sustained performance in dynamic environments. As a working paper, the study focuses on illustrating system behavior under controlled scenarios. Future research will extend this framework toward empirical validation and large-scale optimization models, including integration with real data streams, advanced machine learning architectures, and scenario-based decision models. Further work will also explore quantitative viability metrics and their application in complex agro-industrial and multi-echelon supply chains.

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