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RESEARCH ARTICLE

Generative AI Updates, Organizational Adaptation, and Enterprise Process Stability

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Abstract

Generative artificial intelligence (GenAI) is increasingly embedded in enterprise workflows, yet the models that support these workflows are updated at discrete and sometimes frequent intervals. Each update can improve technical effectiveness while simultaneously invalidating prompts, interfaces, controls, and employee routines. This study develops an impulsive dynamical system to analyze the resulting tension between technical improvement and organizational disruption. The continuous subsystem tracks enterprise process stability, organizational adaptation, and effective model capability between updates. The impulsive subsystem represents the instantaneous effects of a model release on workflow stability, learning, cognitive overload, and technical performance. Positive invariance of the state space is established, the existence of at least one periodic operating trajectory is proved, a closed-form periodic solution for the technical-effectiveness subsystem is derived, and a local stability condition is formulated through the spectral radius of the one-cycle Poincaré map. Numerical experiments compare high-frequency incremental updates, low-frequency major updates, higher governance investment, and cognitive-overload conditions. A long-run performance objective is then used to identify a joint update interval, update intensity, and governance investment policy. The results show that update interval and update intensity should not be selected independently. Small but frequent updates reduce the amplitude of process disruption but may impose persistent coordination costs, whereas large infrequent updates produce deeper stability losses. Organizational adaptation expands the robust operating region, while cognitive overload contracts it. Under the normalized baseline calibration, the best grid policy combines a moderate update interval, a moderate update intensity, and relatively high governance investment. The paper contributes a formal framework for treating GenAI model releases as organizational impulses rather than as purely technical upgrades.

Keywords: generative artificial intelligence, impulsive dynamical system, organizational adaptation, process stability, optimal update policy.

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1 Introduction

Generative artificial intelligence is moving from isolated experimentation toward direct participation in enterprise processes. Large language models and related foundation models now support document preparation, customer interactions, knowledge retrieval, software development, compliance review, and operational decision support. This development extends earlier visions of AI-augmented business process management, in which process-aware systems become more adaptive, context-sensitive, and proactive [1]. Recent work also suggests that the next generation of business process management will move from conventional automation toward greater conversational interaction and operational autonomy [2].

The organizational consequences of this transition cannot be understood only through adoption decisions. Once a GenAI model is connected to a workflow, the model continues to change. Providers release new model versions, organizations modify system prompts, retrieval sources are refreshed, safety layers are replaced, and application programming interfaces are revised. Foundation-model systems may therefore achieve rapid technical improvement while creating recurrent maintenance and validation requirements for the enterprise systems that depend on them [3, 4]. Because the same foundation model is adapted across many downstream applications, any update to the base model propagates simultaneously to all dependent workflows, amplifying the organizational scope of each release [4]. Process-oriented GenAI research has emphasized new opportunities for automation and process redesign, but it has also identified reliability, validation, and human oversight as unresolved problems [5, 6].

A model update is not equivalent to a conventional software patch. A deterministic software module should preserve defined functions unless its specification is deliberately changed. A GenAI model may exhibit different wording, reasoning patterns, refusal behavior, tool-use sequences, or sensitivity to prompts even when the surrounding application remains unchanged. These changes can improve performance on some tasks and reduce it on others. They can also make established prompt templates, review procedures, escalation rules, or employee expectations obsolete. Research on large language models in business process management has consequently highlighted both their generative flexibility and the difficulty of maintaining dependable process behavior [7, 8]. Benchmark studies similarly show that model quality varies with process complexity, task formulation, and evaluation criteria [9].

This creates a managerial timing problem. Updating too slowly may leave the organization with an obsolete model, lower accuracy, weak security, or inferior functionality. Updating too quickly may prevent employees, workflow designers, and control functions from learning how the current version behaves. A large update may deliver a substantial capability gain while causing a pronounced short-term fall in process stability. A sequence of small updates may avoid a severe one-time disruption but create continuous adaptation demands. The relevant decision is therefore not simply whether to update, but how often to update, how much technical change to introduce at each update, and how much organizational adaptation capacity to build before and after each update.

Empirical research confirms that organizational readiness and change capacity shape AI implementation. Studies of GenAI adoption link organizational performance to governance, ethical design, and organizational innovativeness [10]. Case evidence from professional service firms shows that AI readiness, technical constraints, firm size, and the regulatory environment jointly influence adoption depth [11]. A recent mixed-methods study further identifies staff skills and organizational change capacity as central conditions for moving beyond limited GenAI experimentation [12]. These findings indicate that technical capability and organizational capability should be modeled as interacting variables rather than as independent inputs. Experimental evidence further shows that the performance gains from GenAI assistance are heterogeneous across tasks and workers, implying that the organizational impact of each model update will also vary depending on workflow type and employee experience [13, 14].

Business process research has long recognized that external shocks can force rapid changes in process structures, capabilities, and governance arrangements [15]. GenAI model releases differ from purely external shocks because the organization can partly control whether, when, and how strongly they enter production. Nevertheless, an update can have a shock-like effect at the moment of deployment. The workflow then undergoes a continuous recovery and learning process until the next release. This alternation between continuous organizational adjustment and discrete technical intervention naturally suggests an impulsive dynamical system.

Impulsive differential equations are designed for systems whose states evolve continuously except at specific moments when one or more variables jump. Such models have been used to represent abrupt control actions, interventions, collisions, and periodic treatments. Recent surveys emphasize their suitability for systems combining continuous dynamics with event-driven or scheduled actions [16]. Modern stability research also provides tools for evaluating whether the interaction between continuous flow and discrete impulses produces convergence, periodic behavior, or instability [17, 18]. Despite this methodological fit, enterprise GenAI updates have not yet been formally studied as recurring organizational impulses.

This study addresses that gap by developing a three-state impulsive model. The states are enterprise process stability, organizational adaptation, and effective model capability. Between updates, process stability can recover, organizational adaptation can improve through training and problem-driven learning, and model effectiveness can decay as business requirements and technical conditions evolve. At each update, model effectiveness jumps upward, process stability may fall, and organizational adaptation may either improve through learning or deteriorate through cognitive overload. The model is used to answer four questions:

- Under what conditions do enterprise process stability, organizational adaptation, and model effectiveness remain within economically meaningful bounds?
- When does a sequence of periodic updates generate a stable recurring operating trajectory rather than cumulative disruption?
- How do the update interval, update intensity, governance investment, and cognitive overload alter the robust operating region?
- What combination of update interval, update intensity, and governance investment maximizes a normalized long-run performance criterion?

The paper makes four contributions. First, it conceptualizes a GenAI model update as a joint technical and organizational impulse. Second, it integrates process stability, adaptation capacity, and model effectiveness within one nonlinear system. Third, it derives analytical conditions for boundedness, periodic operation, and local stability. Fourth, it develops an optimization framework that treats governance investment as a complement to update timing rather than as an after-the-fact control.

The remainder of the paper is organized as follows. Section 2 reviews research on GenAI-enabled process management, organizational adaptation, model maintenance, and impulsive systems. Section 3 states the assumptions and formulates the continuous and impulsive dynamics. Section 4 develops the mathematical analysis. Section 5 presents numerical simulations and robustness comparisons. Section 6 formulates and solves the long-run update-policy problem. Section 7 discusses theoretical and managerial implications. Section 8 concludes.

2 Literature Review and Research Gap

2.1 GenAI and enterprise process transformation

The relationship between AI and business process management has evolved from rule-based automation toward systems that can interpret unstructured information and generate context-dependent actions. AI-augmented business process management systems are expected to combine process knowledge with data-driven capabilities, allowing processes to respond more flexibly to changing conditions [1]. More recent accounts describe three related shifts: from transactions toward conversations, from automation toward autonomization, and from process models toward process representations that are increasingly generated and revised by AI [2].

Foundation models intensify these shifts because the same model can participate in many tasks. Enterprise automation systems can use multimodal models to understand workflow descriptions, interact with interfaces, and complete tasks that previously required specialized automation scripts [3]. ProcessGPT and related proposals illustrate how generative models may support process discovery, modeling, redesign, and execution [5]. The large process model (LPM) vision goes further by proposing systems that combine the generative capacity of foundation models with process knowledge and formal reasoning [6]. The rapid diffusion of ChatGPT-era models into enterprise contexts has been recognized as creating both new automation opportunities and new demands for continuous process adjustment as model capabilities evolve [19]. Empirical monitoring of production deployments further shows that the behavior of the same model service can change substantially between versions, with performance on specific tasks declining or improving across releases [20].

The new flexibility also creates new forms of process uncertainty. Large language models do not guarantee identical outputs under all conditions, and their responses depend on prompts, context windows, retrieval sources, temperature settings, and model versions. Research on large language models for business process management identifies hallucination, limited process awareness, confidentiality risk, and insufficient explainability as significant barriers [7]. Conversational process modeling studies similarly show that natural-language interaction can reduce modeling effort while introducing ambiguity and verification requirements [8]. Evaluations of model-generated process representations demonstrate that syntactic correctness does not ensure semantic or operational correctness [9].

These limitations are particularly important after a model update. A workflow may have been validated against one model version, but a later version may interpret the same instruction differently. The surrounding organization must then revalidate outputs, modify controls, update documentation, and retrain users. The model can be technically stronger and operationally less stable at the same time. Current research recognizes the need for trustworthy AI, human validation, and process-aware safeguards, but it rarely represents the temporal sequence through which an organization absorbs repeated model changes [3, 7]. Forward-looking syntheses further identify the governance of repeated model updates, output reliability, and organizational adaptation as priority research directions for GenAI management [21].

2.2 Organizational adaptation and implementation capacity

GenAI implementation is a socio-technical process. Technical capability creates potential value, but realized value depends on organizational structures, employee skills, governance, and task redesign. Survey evidence indicates that institutional pressures and ethical design considerations influence organizational GenAI use, while organizational innovativeness changes the performance effect of that use [10]. Multiple-case evidence suggests that firms with stronger readiness and more formal innovation-management arrangements can address technical constraints more effectively [11]. Field evidence further indicates that the gains from GenAI assistance depend on worker experience and task type [14, 22], suggesting that when a model update shifts the capability frontier, the distributional consequences across employees and processes will also change, compounding the organizational adaptation challenge.

Change capacity becomes especially important when a technology evolves after adoption. Mixed-methods evidence shows that complexity, skills, and organizational change capacity are interconnected in GenAI adoption [12]. Human-AI collaboration research further shows that automation and augmentation are interdependent forces: overemphasizing either can undermine the organizational complementarities needed to translate model capability into stable process performance [24]. These findings imply that organizations do not merely receive model capability. They translate that capability through accumulated knowledge, training, governance routines, and process-specific learning. Interview-based evidence further identifies five readiness categories—including assets, capabilities, and organizational commitment—that determine whether a firm can successfully translate AI adoption into sustained operational value [25].

Adaptation has both proactive and reactive components. Proactive adaptation includes training, sandbox testing, documentation, prompt governance, and staged release procedures. Reactive adaptation occurs when process failures reveal previously unknown weaknesses. A failed output can lead to revised controls, new escalation rules, or additional employee learning. Exogenous-shock research in business process management similarly argues that organizations need capabilities for rapid process diagnosis, redesign, and stabilization after disruptive events [15].

Adaptation can also be constrained by cognitive overload. Frequent releases may require employees to relearn interfaces and revise established mental models before the previous version has become familiar. A process team may spend more time testing and explaining model behavior than exploiting its capability. The effect is not necessarily visible in aggregate adoption measures because the organization can report widespread use while experiencing recurring operational friction. Qualitative evidence from knowledge-intensive firms confirms that AI tools simultaneously introduce cognitive strain and psychobehavioral burdens that partially offset their coordination and decision-making gains [23]. A dynamic model should therefore allow an update to create learning and overload simultaneously.

2.3 Model maintenance, monitoring, and degradation

The operationalization of machine learning has produced a substantial literature on machine learning operations. MLOps integrates development, deployment, monitoring, versioning, and continuous improvement in order to reduce the gap between experimental models and dependable production systems [26]. Empirical work on MLOps adoption identifies technical, operational, organizational, and business challenges, including model complexity and cross-functional coordination [27]. Research on engineering practices for machine-learning systems likewise shows that deployment and maintenance require systematic practices beyond conventional software development [28].

Monitoring is essential because a model that performed well at deployment may later become less effective. Production-monitoring frameworks track data drift, prediction drift, and performance change so that organizations can identify when a model requires investigation or replacement [29]. Concept-drift research distinguishes changes in data distributions, relationships, and performance, and it emphasizes that model degradation may occur gradually rather than at an easily observed moment [30].

GenAI systems create additional maintenance challenges. Their effective performance depends not only on model weights but also on prompts, retrieval data, tools, safety policies, and user behavior. Consequently, the effective capability experienced by an enterprise can decay even when the underlying model remains available. Business requirements change, organizational knowledge becomes outdated, and competing models improve. The present study represents this process through a continuous decay rate for effective model capability between updates.

Existing maintenance research is usually organized around pipelines and engineering practices. It does not generally model the feedback from model updates to organizational adaptation or process stability. An update is treated as a technical deployment event, while the temporary disruption of routines is left outside the analytical system. This omission matters because update decisions can appear technically optimal while being organizationally destabilizing. Broader information-systems scholarship likewise identifies organizational skills, transparency, governance, and task-specific validation as central conditions for responsible GenAI implementation [31].

2.4 Impulsive dynamical systems

An impulsive system combines continuous evolution with discrete state changes. A general representation is

$$\dot{X}(t) = F(X(t)),\ t \neq t_k, \qquad X_k^{\text{post}} = J(X_k^{\text{pre}}),\ t = t_k, \tag{1}$$

where t_k denotes the kth impulse, F governs the continuous flow, and J is the jump map. The framework is appropriate when a system evolves continuously between interventions but experiences an abrupt change when an intervention occurs [16].

Recent stability research has developed dwell-time and Lyapunov conditions for nonlinear impulsive systems [17]. Periodic and non-instantaneous impulsive equations have also been analyzed through fixed-point and Cauchy-matrix approaches [18]. These studies show that system stability depends jointly on the continuous dynamics, the jump magnitude, and the time between impulses. A stabilizing continuous process can be overwhelmed by impulses that are too frequent or too strong, while a beneficial impulse may compensate for gradual deterioration. Related studies examine stochastic nonlinear delay systems subject to multiple periodic impulses, showing that the combined action of impulsive disturbance and impulsive control determines global stability [32]. Alongside these mathematical developments, enterprise-level evidence shows that AI system updates impose simultaneous cognitive and coordination burdens on employees, a dynamic that must be reflected in any operationally meaningful stability model [23]. Self-triggered comparison system approaches and event-triggered delayed impulsive control provide complementary existence and stability results for nonlinear impulsive systems [33, 34].

The same logic applies to enterprise model updates. Organizational learning and process recovery occur continuously, but the deployment of a materially different model changes several states at once. The update can be beneficial for model capability and detrimental for immediate process stability. Stability therefore cannot be inferred from the update effect

Table 1. Definitions and baseline values of variables and parameters.

Symbol	Definition	Range	Baseline
$x(t)$	Enterprise process stability	$[0, 1]$	Endogenous
$y(t)$	Organizational adaptation to the deployed model	$[0, 1]$	Endogenous
$z(t)$	Effective capability of the deployed GenAI model	$[0, 1]$	Endogenous
T	Interval between production updates	$T > 0$	4.00
θ	Effective update intensity	$(0, 1]$	0.35
a	Natural process-recovery rate	≥ 0	0.25
b	Adaptation-assisted recovery coefficient	≥ 0	0.35
c	Technology-organization mismatch coefficient	≥ 0	0.40
g	Governance and training investment rate	≥ 0	0.12
d	Problem-driven learning coefficient	≥ 0	0.20
m	Adaptation depreciation rate	≥ 0	0.08
ν	Effective model obsolescence rate	≥ 0	0.05
η	Learning gain created by an update	≥ 0	0.30
ω	Cognitive-overload coefficient	≥ 0	0.08
χ	Conversion of update intensity into capability gain	$(0, 1]$	0.60
α	Capability-stability complementarity weight	> 0	1.50
β	Process-instability penalty coefficient	≥ 0	1.00
γ	Technology-organization mismatch penalty coefficient	≥ 0	0.40
κ	Governance-investment cost coefficient	> 0	2.00
C_0	Fixed production-release cost	≥ 0	0.12
C_1	Intensity-dependent update-cost coefficient	≥ 0	0.90

alone. It must be evaluated over the complete cycle from one update to the next.

2.5 Research gap and modeling position

The reviewed literature provides four pieces of the problem. Process research explains how GenAI can transform enterprise workflows. Adoption research establishes the role of organizational readiness and change capacity. MLOps research explains why deployed models require monitoring and maintenance. Impulsive-systems research provides methods for analyzing repeated discrete interventions. These streams have not yet been integrated into a formal model of recurring GenAI releases.

The present model is intentionally parsimonious. It does not attempt to represent every feature of a production GenAI stack. Instead, it isolates the dynamic tradeoff between three aggregate states: stable process execution, organizational capacity to work with the current model, and the effective capability of the deployed model. This abstraction allows the paper to derive interpretable stability and optimization results while retaining direct relevance to enterprise update policy.

3 Model Assumptions and Formulation

3.1 System setting

Consider an enterprise that has embedded a GenAI application in one or more recurring business processes. The application may support customer service, document review, internal knowledge search, procurement, marketing, or managerial analysis. The organization chooses whether to deploy a new model version at scheduled times $t_k = kT$, where $T > 0$ is the update interval. Each deployment has an intensity $0 < \theta \leq 1$, which represents the effective magnitude of technical and behavioral change introduced into production.

A small θ can represent an incremental model revision, a limited prompt change, or a narrow rollout. A large θ can represent a major model replacement, substantial tool-use changes, or a broad enterprise release. Update intensity is therefore not identical to a provider's version number. It measures how much of the changed technical system is exposed to the focal process. Let

$$X(t) = \big(x(t), y(t), z(t)\big)^\top \in [0, 1]^3, \qquad (2)$$

where $x(t)$ is enterprise process stability, $y(t)$ is organizational adaptation, and $z(t)$ is effective model capability. Higher values are desirable for each state, but a high $z(t)$ can create mismatch pressure when $y(t)$ is low.

The values in Table 1 are normalized scenario parameters rather than estimates from a specific company. Their purpose is to demonstrate the qualitative behavior of the model and to compare update policies under consistent assumptions. The results should therefore be interpreted as conditional mathematical findings, not as direct predictions for an individual enterprise.

3.2 Continuous dynamics between updates

Between update times, the system follows

$$\begin{aligned}\dot{x} &= a(1-x) + by(1-x) - cz(1-y)x,\\ \dot{y} &= g(1-y) + d(1-x)(1-y) - my,\\ \dot{z} &= -\nu z.\end{aligned} \tag{3}$$

The first equation in system (3) contains three mechanisms. The term $a(1-x)$ represents natural recovery through existing routines, troubleshooting, and process correction. The term $by(1-x)$ represents additional recovery generated by organizational adaptation. The term $cz(1-y)x$ represents technology-organization mismatch. A capable model creates greater potential process change, but that change becomes disruptive when the organization has not adapted to it.

The mismatch term is not intended to imply that model capability is intrinsically harmful. If y is close to one, the term approaches zero and the organization can use a technically strong model without substantial destabilization. If y is low, the same model can produce inconsistent work practices, higher review burdens, and uncertain escalation decisions. This structure captures the idea that realized process performance depends on the alignment between technology and organizational capability.

The second equation in system (3) models organizational adaptation. The term $g(1-y)$ represents planned capability building through governance, training, testing, documentation, and support. The term $d(1-x)(1-y)$ represents problem-driven learning. Process instability exposes gaps and can motivate corrective learning. The term my represents forgetting, staff turnover, skill depreciation, and the obsolescence of procedures.

The third equation in system (3) assumes exponential decay in effective model capability between updates. For the interval from one update time to the next, the solution is

$$z(t) = z_k^{\text{post}}\, e^{-\nu(t-t_k)}. \tag{4}$$

The decay rate ν is an aggregate parameter. It can reflect changing business requirements, deteriorating retrieval content, new compliance requirements, competitor improvement, or the declining fit of the current model to the organization's task environment.

3.3 Impulsive update mechanism

At each update time $t_k = kT$, the states jump according to the following system. For compactness, the superscripts "pre" and "post" identify states immediately before and after the kth update.

$$\begin{aligned}x_k^{\text{post}} &= x_k^{\text{pre}}\big(1-\theta(1-y_k^{\text{pre}})\big),\\ y_k^{\text{post}} &= y_k^{\text{pre}} + \theta\big(\eta(1-y_k^{\text{pre}}) - \omega y_k^{\text{pre}}\big),\\ z_k^{\text{post}} &= z_k^{\text{pre}} + \chi\theta(1-z_k^{\text{pre}}).\end{aligned} \tag{5}$$

The first relation in jump system (5) gives the immediate update-induced change in process stability. The loss is

$$D_k = x_k^{\text{pre}} - x_k^{\text{post}} = \theta x_k^{\text{pre}}(1-y_k^{\text{pre}}). \tag{6}$$

The disruption increases with update intensity and decreases with organizational adaptation. A highly prepared organization can absorb a substantial update with a smaller loss of process stability.

The second relation in jump system (5) allows the update to create both learning and overload. Its positive component represents learning opportunities, new documentation, and capability development, whereas its negative component represents the destruction of previously useful routines and the cognitive burden imposed on adapted users. A major update can therefore improve adaptation when existing capability is low and reduce it when much of the existing capability becomes obsolete.

The third relation in jump system (5) gives the technical benefit of the update. The capability gain is larger when the existing model is weak and approaches zero as z approaches one. The parameter χ accounts for incomplete translation of a vendor-side model improvement into enterprise-specific value.

Figure 1 summarizes the causal structure. The principal modeling assumptions and their organizational interpretations are summarized in Table 2.

Table 2. Model assumptions and impulsive mechanisms.

Assumption	Mathematical representation	Organizational interpretation
Process recovery is bounded	$a(1-x)+by(1-x)$	Recovery slows as stability approaches its upper bound.
Technical-organizational mismatch is conditional	$-cz(1-y)x$	A strong model is disruptive mainly when adaptation is weak.
Adaptation is planned and experiential	$g(1-y)+d(1-x)(1-y)$	Training and operational problems both produce learning.
Adaptation depreciates	$-my$	Skills and procedures lose value over time.
Effective model capability decays	$-\nu z$	Task fit and contextual relevance deteriorate between updates.
An update creates immediate disruption	$\theta x_k^{\text{pre}}(1-y_k^{\text{pre}})$	More intensive updates are harder to absorb.
An update creates learning and overload	$\theta(\eta(1-y_k^{\text{pre}})-\omega y_k^{\text{pre}})$	Releases can build capability and invalidate prior knowledge.
Capability gain has diminishing returns	$\chi\theta(1-z_k^{\text{pre}})$	A strong existing model receives a smaller marginal gain.

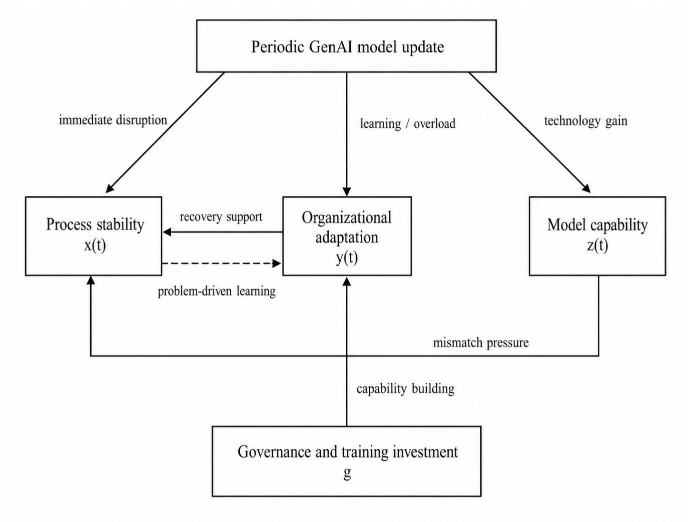

Figure 1. Conceptual structure of the enterprise GenAI update system.

3.4 Long-run performance criterion

A firm should not maximize technical capability in isolation. Let the instantaneous operating contribution be

$$\pi(t)=\alpha x(t)z(t)-\beta(1-x(t))^2-\gamma z(t)(1-y(t))-\kappa g^2, \tag{7}$$

where $\alpha>0$ measures the complementarity between stable processes and effective model capability, $\beta>0$ measures the cost of instability, $\gamma>0$ measures the cost of mismatch, and $\kappa>0$ measures the convex cost of governance investment.

The long-run normalized performance index is

$$\Pi(T,\theta,g)=\liminf_{N\to\infty}\frac{1}{NT}\int_0^{NT}\pi(t)\,dt-\frac{C_0+C_1\theta^2}{T}, \tag{8}$$

where C_0 is the fixed cost of a production release and $C_1\theta^2$ is the intensity-dependent validation, migration, and coordination cost. Dividing update costs by T converts them into a long-run rate. The enterprise update problem is

$$\max_{T,\theta,g}\Pi(T,\theta,g),\ T\in[T_L,T_U],\ \theta\in[\theta_L,\theta_U],\ g\in[g_L,g_U]. \tag{9}$$

The bounded decision set reflects practical limits on update cadence, release scope, and governance spending, where $[T_L,T_U]$, $[\theta_L,\theta_U]$, and $[g_L,g_U]$ denote the admissible ranges for the interval, intensity, and governance rate, respectively; numerical values are specified in Section 5.

4 Mathematical Analysis

4.1 Positive invariance and boundedness

The first requirement is that the states remain within $[0,1]$. This is necessary for both mathematical consistency and organizational interpretation.

Theorem 1. *Suppose all continuous parameters are nonnegative,* $0<\theta\le 1$, $0<\chi\le 1$, *and* $\theta(\eta+\omega)\le 1$. *If* $X_0\in[0,1]^3$, *then* $X(t)\in[0,1]^3$ *for all* $t\ge 0$.

Proof. Consider the continuous dynamics on the boundary of the unit cube. The inward-pointing conditions on the x- and y-boundaries are

$$\begin{aligned}\dot{x}\big|_{x=0} &= a + by \geq 0, & \dot{x}\big|_{x=1} &= -cz(1-y) \leq 0,\\ \dot{y}\big|_{y=0} &= g + d(1-x) \geq 0, & \dot{y}\big|_{y=1} &= -m \leq 0.\end{aligned} \tag{10}$$

These inequalities show that the continuous flow cannot cross below zero or above one through the x- and y-boundaries.

For z, the third equation in system (3) preserves nonnegativity and cannot increase a state above one.

It remains to examine the jump map. Under the stated bounds, the multiplicative factor in the first relation of system (5) lies in $[0,1]$, so the post-update process-stability state remains in $[0,1]$. The third relation is a convex combination of the pre-update capability and one, so the post-update capability also remains in $[0,1]$. The second relation can be written as

$$y_k^{\text{post}} = \big(1 - \theta(\eta+\omega)\big)y_k^{\text{pre}} + \theta\eta. \tag{11}$$

Under the condition stated in Theorem 1, both the coefficient and intercept in equation (11) are nonnegative. Over the admissible pre-update adaptation range, the maximum post-update value is $1 - \theta\omega \leq 1$. Hence, the jump map also preserves the unit cube. □

Theorem 1 ensures that the normalized states remain meaningful without artificial truncation. It also allows the use of compactness in the periodic-solution analysis.

4.2 One-cycle map and periodic operating trajectory

Let $\Phi_T(X)$ denote the state reached after the continuous flow of duration T, starting immediately after an update. Let J_θ denote the jump map defined by system (5). The one-cycle Poincaré map is

$$P_{T,\theta}(X) = J_\theta\big(\Phi_T(X)\big). \tag{12}$$

A fixed point X_p of $P_{T,\theta}$ corresponds to a T-periodic operating trajectory. The state immediately after every update is the same, and the trajectory between updates repeats.

Theorem 2. *Under the assumptions of Theorem 1, the map $P_{T,\theta}$ has at least one fixed point in $[0,1]^3$.*

Proof. The vector field in system (3) is continuously differentiable on the unit cube, so the flow map Φ_T is continuous. The jump map is continuous. Theorem 1 shows that the composition maps the compact convex set $[0,1]^3$ into itself. Brouwer's fixed-point theorem therefore guarantees at least one fixed point. □

The theorem establishes existence, not uniqueness or stability. Multiple periodic operating trajectories may exist under strongly nonlinear parameter combinations. The numerical analysis evaluates the locally attracting trajectory reached from representative initial states.

The technical-effectiveness subsystem is independent of x and y, which allows a closed-form periodic solution. Let z_k^{post} denote capability immediately after update k. The pre-update decay and post-update jump over one cycle satisfy

$$\begin{aligned} z_{k+1}^{\text{pre}} &= z_k^{\text{post}} e^{-\nu T},\\ z_{k+1}^{\text{post}} &= (1-\chi\theta)e^{-\nu T} z_k^{\text{post}} + \chi\theta. \end{aligned} \tag{13}$$

Proposition 1. *If $T > 0$, $\nu \geq 0$, and $0 < \chi\theta \leq 1$, the technical-effectiveness subsystem has a unique globally attracting periodic orbit with*

$$z_*^{\text{post}} = \frac{\chi\theta}{1-(1-\chi\theta)e^{-\nu T}}, \qquad z_*^{\text{pre}} = e^{-\nu T} z_*^{\text{post}}. \tag{14}$$

Proof. Equation (13) is an affine contraction because its slope lies in $[0,1)$ under the stated assumptions. Solving $z_{k+1}^{\text{post}} = z_k^{\text{post}}$ yields equation (14). □

Proposition 1 reveals the direct update tradeoff. A shorter T or a larger θ weakly raises the periodic capability level. However, neither expression includes process stability or organizational adaptation. Technical optimization alone therefore tends to favor more frequent or stronger updates than the integrated enterprise objective.

4.3 Local stability of the periodic trajectory

Let X_p be a fixed point of the one-cycle map. The Jacobian of the continuous vector field is

$$DF(x,y,z) = \begin{pmatrix} -a - by - cz(1-y) & b(1-x) + czx & -c(1-y)x \\ -d(1-y) & -g - d(1-x) - m & 0 \\ 0 & 0 & -\nu \end{pmatrix}. \tag{15}$$

Let $\Psi(T; X_p)$ be the fundamental matrix obtained by integrating the variational equation along the periodic continuous trajectory. The Jacobian of the jump map, evaluated at the pre-update state, is

$$DJ_\theta = \begin{pmatrix} 1 - \theta(1 - y_k^{\text{pre}}) & \theta x_k^{\text{pre}} & 0 \\ 0 & 1 - \theta(\eta+\omega) & 0 \\ 0 & 0 & 1 - \chi\theta \end{pmatrix}. \tag{16}$$

The derivative of the one-cycle map is

$$DP_{T,\theta}(X_p) = DJ_\theta\, \Psi(T; X_p). \tag{17}$$

Theorem 3. *The periodic operating trajectory associated with X_p is locally asymptotically stable if*

$$\rho\big(DP_{T,\theta}(X_p)\big) < 1, \tag{18}$$

where $\rho(\cdot)$ denotes spectral radius.

Proof. The result follows from linearization of the discrete one-cycle map. If every eigenvalue lies inside the unit disk, perturbations of the post-update state contract from one update cycle to the next. □

Condition (18) separates local orbit stability from managerial robustness. A periodic trajectory can be locally stable and still operate at an unacceptably low average or minimum process-stability level. For this reason, the numerical analysis reports the spectral radius together with performance-based robust, fragile, and disrupted operating regions.

4.4 Comparative properties

The immediate disruption in equation (6) yields direct comparative results.

Proposition 2. *Holding the pre-update state fixed,*

$$\frac{\partial D_k}{\partial \theta} = x_k^{\mathrm{pre}}(1 - y_k^{\mathrm{pre}}) \geq 0, \qquad \frac{\partial D_k}{\partial y_k^{\mathrm{pre}}} = -\theta x_k^{\mathrm{pre}} \leq 0. \tag{19}$$

Thus, stronger updates increase immediate disruption, while adaptation reduces it.

The update-induced adaptation change and its positive-learning condition are

$$\Delta y_k = \theta\big(\eta - (\eta+\omega) y_k^{\mathrm{pre}}\big), \qquad \Delta y_k > 0 \Leftrightarrow y_k^{\mathrm{pre}} < \frac{\eta}{\eta+\omega}. \tag{20}$$

Equation (20) has an intuitive interpretation. If $\eta+\omega > 0$, the update produces net immediate learning when $y_k^{\mathrm{pre}} < \eta/(\eta+\omega)$ and a net immediate loss of adaptation above that threshold. When $\eta = \omega = 0$, $\Delta y_k = 0$.

The continuous adaptation equilibrium conditional on a fixed x is

$$y_c(x) = \frac{g + d(1-x)}{g + d(1-x) + m}. \tag{21}$$

This expression increases with governance investment and process problems. It decreases with adaptation depreciation. The problem-driven term is beneficial only when the organization can convert failures into learning. In practice, this requires incident review, prompt and output logging, and responsibility for implementing corrective actions.

Proposition 3. *The periodic technical capability z_*^{post} is nondecreasing in θ and nonincreasing in T and ν; the inequalities are strict away from the degenerate no-decay or full-renewal boundaries.*

The proof follows by differentiating equation (14). Proposition 3 explains why a technology-centered policy favors large and frequent updates. Equations (19)–(21) explain why the organizationally optimal policy can differ. Table 3 summarizes the main analytical results and their managerial interpretations.

5 Numerical Simulations

5.1 Numerical procedure and scenario design

The continuous subsystem was solved with a fourth-order Runge-Kutta method. Each update interval was divided into 120 integration steps. The one-cycle map was iterated for up to 200 cycles, and convergence was declared when the maximum absolute change in the post-update state fell below 10^{-10}. The Jacobian of the Poincaré map was approximated with centered finite differences using a perturbation of 10^{-6}. A step-size check using 120, 240, and 480 Runge-Kutta steps per update interval changed the reported long-run performance and state averages by less than 0.001 in absolute value, confirming numerical convergence at the reported three-decimal precision.

The normalized performance parameters were $\alpha = 1.5$, $\beta = 1.0$, $\gamma = 0.4$, $\kappa = 2.0$, $C_0 = 0.12$, and $C_1 = 0.90$. These values place a positive weight on stable use of model capability, impose convex losses for instability, penalize mismatch, and prevent unlimited governance spending. The calibration is illustrative and is not presented as an empirical estimate.

Five comparison scenarios were examined in addition to the optimized policy. The baseline uses $T = 4$, $\theta = 0.35$, and $g = 0.12$. The high-frequency small-update scenario uses $T = 1.5$ and $\theta = 0.18$. The low-frequency large-update scenario uses $T = 8$ and $\theta = 0.70$. The high-governance scenario increases g to 0.20. The high-overload scenario increases ω from 0.08 to 0.30.

Table 3. Main analytical results and interpretations.

Result	Condition or expression	Interpretation
Positive invariance	Theorem 1	Normalized states remain in $[0, 1]$.
Periodic operating trajectory	Fixed point of $P_{T,\theta}$	Repeated updates can generate a recurring long-run cycle.
Technical periodic solution	Equation (14)	Capability depends jointly on update intensity and interval.
Local stability	$\rho(DP) < 1$	Cycle-to-cycle perturbations contract.
Immediate disruption	$D_k = \theta x_k^{\text{pre}}(1 - y_k^{\text{pre}})$	Prepared organizations absorb updates more effectively.
Adaptation threshold	$y_k^{\text{pre}} < \eta/(\eta + \omega)$	An update creates net learning only below the threshold.
Continuous adaptation level	Equation (21)	Governance investment raises adaptation capacity.
Technical update effect	z_*^{post} rises with θ and falls with T	Technical and organizational objectives can diverge.

5.2 Baseline periodic dynamics

Figure 2 shows the periodic trajectory under the baseline parameters. Model effectiveness declines smoothly between releases and jumps upward at each update. Process stability generally recovers between releases but falls at the update times. Organizational adaptation changes more gradually because planned learning and problem-driven learning partly offset depreciation.

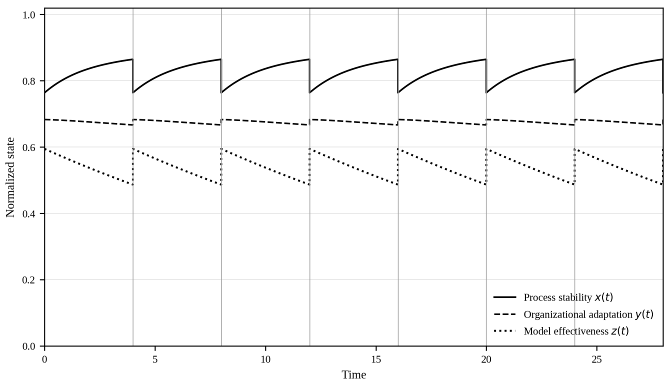

Figure 2. Dynamic trajectories under the baseline scenario.

The baseline converges to a stable recurring cycle. Average process stability is 0.829, and the minimum within-cycle process stability is 0.764. Average adaptation is 0.676, while average model effectiveness is 0.539. The process-stability amplitude (defined as the within-cycle difference between the maximum and minimum of x) is 0.101. These values show why average performance alone is insufficient. An enterprise may report a high average level while still experiencing a material drop after every release.

The periodic pattern is not a defect of the numerical method. It is the expected long-run behavior of a system subject to periodic impulses. The relevant managerial objective is therefore not to eliminate all fluctuation. It is to keep the cycle within an acceptable operating band while maintaining enough model capability to justify the update program.

5.3 Alternative update strategies

Figure 3 compares process-stability trajectories by update cycle. The high-frequency small-update policy produces the smallest within-cycle amplitude. Its minimum process stability is 0.783, which is higher than the baseline minimum. The policy also maintains a higher average model-effectiveness level because capability is refreshed more often.

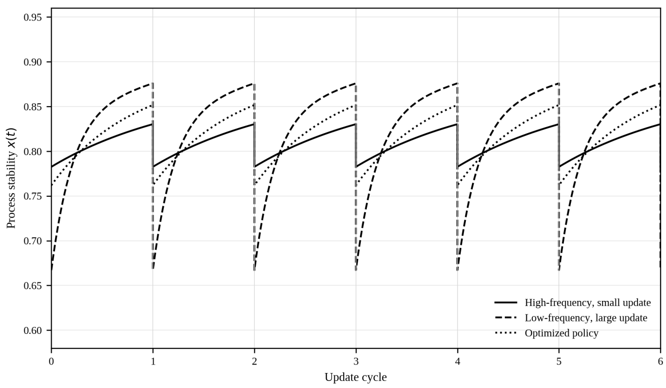

Figure 3. Dynamic comparison of alternative update strategies.

The low-frequency large-update strategy has a similar average process-stability level but a much deeper post-update drop. Its minimum stability is 0.667, and its amplitude is 0.209. This result illustrates an important asymmetry. Long recovery intervals can support a reasonable average, yet a major release can create a severe short-term operational risk. Organizations that evaluate only quarterly or annual average performance may overlook this exposure.

The high-governance scenario increases average process stability to 0.866 and raises the minimum to 0.814. It also increases average adaptation to 0.744. The performance gain is moderate because governance investment is costly in the objective function, but the reduction in downside instability is substantial. Governance should therefore be evaluated partly as resilience investment rather than only through its effect on average productivity.

The high-cognitive-overload scenario reduces average adaptation from 0.676 to 0.633. Average process stability falls to 0.808, the minimum within-cycle process stability falls to 0.743, and the performance index declines from 0.483 to 0.449. This comparison shows that the same formal update schedule can have different results depending on whether the organization preserves or destroys useful routines during each release.

5.4 Robust operating regions

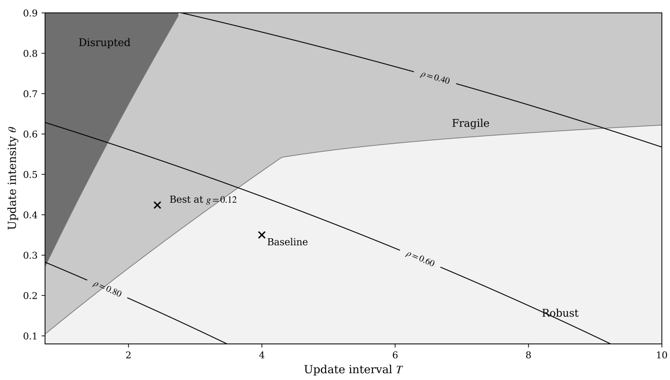

Figure 4. Robust operating regions in the update-interval–update-intensity plane.

Figure 4 maps update interval and update intensity at the baseline governance level. The classification uses two operational thresholds. A point is labeled robust when mean process stability is at least 0.80 and minimum process stability is at least 0.70. It is labeled fragile when mean stability is at least 0.72 and minimum stability is at least 0.58. Other points are labeled disrupted. These thresholds are managerial screening criteria rather than additional mathematical stability conditions. Varying all four screening thresholds by $\pm5\%$ preserved the same qualitative robust-fragile-disrupted geometry and the location of the robust region.

The robust region is concentrated at moderate or long intervals with low-to-moderate update intensity. Very short intervals combined with strong updates create disrupted operation because the organization receives another shock before the prior one has been absorbed. Large updates can remain feasible when the interval is long enough, but they often move the system into the fragile region because the minimum stability becomes low.

The spectral-radius contours provide a different type of information. Across the plotted grid, the computed spectral radius ranges from approximately 0.279 to 0.917. The periodic orbit is therefore locally attracting throughout the selected domain. Nevertheless, part of the domain is managerially disrupted. This distinction is important: convergence to a low-quality cycle is still convergence. Mathematical stability should not be interpreted as acceptable enterprise performance.

The best conditional performance point at $g = 0.12$ lies near $T = 2.4$ and $\theta = 0.42$. It is more intensive than the baseline but still avoids the extreme upper-left region, where strong updates arrive too quickly. The shape of the region confirms that update interval and update intensity are complements. A release policy should specify both variables rather than relying on a generic instruction to update frequently or conservatively.

6 Optimal Update Policy

6.1 Optimization design

The bounded optimization problem in equation (9) was evaluated over $T \in [0.75, 7.00]$, $\theta \in [0.08, 0.80]$, and $g \in [0.04, 0.20]$. A coarse three-dimensional grid search was first conducted to identify the promising region of the decision space. The update interval and intensity were then evaluated on a denser grid at the best governance level.

Because the long-run objective is generally nonconvex and nonconcave owing to bilinear state interactions and the nonlinear dependence of the periodic trajectory on the decision variables, the policy is identified through bounded grid-based search rather than first-order optimality conditions alone. The objective contains three central tradeoffs. First, shorter intervals raise model effectiveness but increase fixed release costs. Second, larger update intensity raises capability but increases both immediate disruption and intensity-dependent update costs.

Table 4. Simulation scenarios and comparative results.

Scenario	T	θ	g	Performance	Mean x	Minimum x
Baseline	4.00	0.350	0.12	0.483	0.829	0.764
High-frequency small update	1.50	0.180	0.12	0.491	0.809	0.783
Low-frequency large update	8.00	0.700	0.12	0.490	0.823	0.667
High governance investment	4.00	0.350	0.20	0.489	0.866	0.814
High cognitive overload	4.00	0.350	0.12	0.449	0.808	0.743
Optimized policy	2.34	0.430	0.20	0.566	0.814	0.760

Third, governance investment increases adaptation and stability but has a convex cost. These competing effects make an interior solution plausible for update timing and intensity, while the optimal governance level depends on the admissible investment range.

6.2 Performance surface and best grid policy

Figure 5 shows the performance surface at $g = 0.20$. The best grid point occurs at approximately $T = 2.34$ and $\theta = 0.430$, with a long-run performance index of 0.566. The corresponding grid-optimal policy is reported in Table 4.

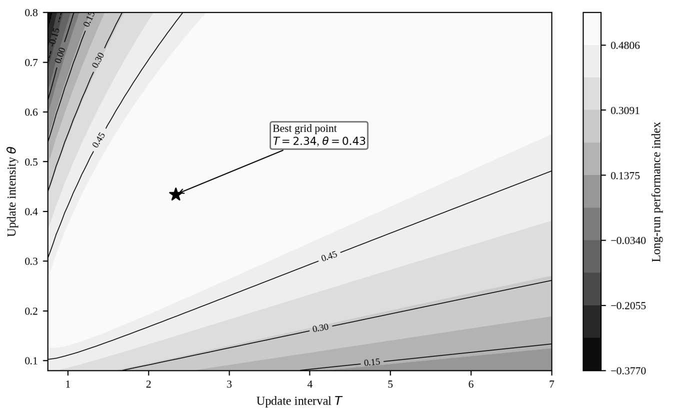

Figure 5. Long-run performance and the optimal update policy.

The optimized policy does not maximize mean process stability. Its mean stability of 0.814 is lower than the high-governance baseline value of 0.866. It delivers a higher objective because mean model effectiveness rises to 0.716. This is a deliberate feature of the model. An optimal enterprise policy should not preserve stability by avoiding useful technical change. It should accept controlled disturbance when the resulting capability gain exceeds the disruption and update costs.

The policy also avoids the highest update intensity. Very strong releases increase technical capability, but the marginal gain becomes small as z approaches one. At the same time, disruption and validation costs continue to increase. This produces a moderate optimal intensity. The optimal interval is shorter than the baseline because higher governance investment allows the organization to absorb updates more effectively.

6.3 A readiness-conditioned decision rule

The fixed-period model can be translated into a practical release rule. Before deployment, the enterprise can estimate a readiness score corresponding to y_k^{pre}. Equation (6) provides a direct upper bound on acceptable update intensity when the organization sets a maximum immediate disruption $\bar{D}$:

$$0 < \theta \le \min\left(1, \frac{\bar{D}}{x_k^{\text{pre}}(1 - y_k^{\text{pre}})}\right). \tag{22}$$

For $x_k^{\text{pre}}(1 - y_k^{\text{pre}}) > 0$, equation (22) applies directly; if this product is zero, $D_k = 0$ and the disruption constraint is automatically satisfied. When readiness is low, the allowable release intensity should be reduced. The organization can either stage the release, increase pre-release training, or delay the update. When readiness is high, the same disruption limit permits a larger update.

A second rule follows from equation (20). If existing adaptation exceeds $\eta/(\eta + \omega)$, a release is expected to reduce adaptation immediately. This does not imply that the release should be rejected. It implies that the enterprise should identify which procedures will become obsolete and explicitly replace them. Documentation migration, prompt revalidation, and role-specific training should be treated as components of the release rather than as later remediation.

A third rule concerns post-release monitoring. Because the system is periodic, evaluation should distinguish the minimum, the recovery rate, and the average. A policy that improves the average while producing an unacceptable minimum may be unsuitable for high-risk processes. Conversely, a small temporary decline may be acceptable when recovery is rapid and the capability gain is large.

7 Discussion

7.1 Theoretical implications

The analysis extends research on GenAI-enabled process management in three ways. First, it shifts attention from initial adoption to recurrent technological change. Much of the organizational AI literature asks why firms adopt or how adoption influences performance [10, 11]. The present model begins after adoption and treats the deployed system as a moving target. This is increasingly relevant as enterprise workflows depend on externally updated foundation models.

Second, the model formalizes the complementarity between technical capability and organizational adaptation. Process stability depends not only on the absolute level of model capability but also on its alignment with organizational capability. This extends socio-technical arguments by providing a nonlinear mismatch term and an explicit update shock. A technically stronger model can create a temporary deterioration in process stability when the organization lacks the knowledge and controls required to use it.

Third, the paper introduces a periodic operating trajectory as a more realistic long-run outcome than a static equilibrium. Enterprise GenAI systems may never reach a permanent steady state because updates repeatedly alter the environment. The relevant target is a stable and acceptable cycle. This perspective connects business process research with impulsive dynamical systems and highlights the role of the one-cycle Poincaré map.

The distinction between local mathematical stability and managerial robustness is also theoretically useful. The numerical results contain regions in which the periodic orbit is locally attracting but process performance is classified as fragile or disrupted. Stability analysis answers whether perturbations decay. It does not answer whether the trajectory is valuable or safe. Applied mathematical studies of enterprise systems should therefore combine dynamical stability with domain-specific operating constraints.

7.2 Managerial implications

The first managerial implication is that release frequency should not be chosen independently of release scope. A policy of frequent updates can be effective when each update is small and testing is automated. The same frequency can be destabilizing when updates materially change prompts, outputs, or tool behavior. Release governance should therefore report both cadence and effective intensity.

The second implication is that governance investment changes the feasible update frontier. Training, validation, documentation, monitoring, and staged deployment do more than reduce compliance risk [37]. They allow the enterprise to capture technical improvements more quickly. In the model, higher g increases adaptation and reduces the magnitude of update-induced process losses. Governance is therefore a productive complement to technical investment. Broader AI scholarship identifies organizational skills, governance readiness, and institutional capacity as foundational conditions for reliable AI deployment [35]; in the update-cycle context, these same conditions determine how quickly an organization can restore process stability after each release. Applied governance frameworks operationalize these conditions through training, standards, and executable organizational processes that span the AI system lifecycle [36], and the present model adds the temporal proposition that such frameworks must be synchronized with the release interval to be effective.

The third implication is that average performance should not be the only update metric. The low-frequency large-update scenario has an acceptable average but a much lower minimum process-stability level. For customer-facing, financial, safety, or compliance processes, the minimum may determine whether the strategy is acceptable. Organizations should monitor post-release error rates, manual override rates, exception queues, and recovery time.

The fourth implication concerns cognitive overload. A release can generate useful learning, but it can also invalidate employee knowledge. Organizations should reduce overload by maintaining stable interface conventions, communicating behavior changes, providing role-specific examples, and separating technical experimentation from production release. Frequent changes without structured learning can lower adaptation even when employees receive more exposure to the technology.

The fifth implication is that the enterprise should preserve the ability to delay, limit, or reverse a release. A provider's new model does not need to enter every process immediately. The readiness-conditioned bound in equation (22) can support staged rollouts.

High-risk processes can remain on the previous model while lower-risk processes generate evidence about the new version.

7.3 Relationship to MLOps and process governance

The model complements MLOps rather than replacing it. MLOps provides engineering practices for versioning, testing, monitoring, and deployment [26]. The impulsive model provides a policy layer that asks how those technical actions interact with organizational adaptation and process stability. Monitoring frameworks can supply empirical measures for x, y, and z [29]. For example, process stability can be proxied by task-completion consistency and exception rates, adaptation by override quality and training completion, and effective model capability by validated task performance.

The framework also complements process governance. GenAI releases should be represented as planned process changes with identified owners, affected roles, validation requirements, and rollback criteria. Process-management research increasingly recognizes that AI changes the design and governance of operational work [2, 38]. The present model adds the temporal proposition that governance must be synchronized with the release cycle.

7.4 Limitations and future research

The study has several limitations. First, the model uses three aggregate states. Real enterprises contain multiple departments, processes, user groups, and model components. Future research could extend the system to a network in which process units have different adaptation rates and exchange knowledge.

Second, update times are periodic. In practice, releases may be event-triggered by detected model degradation, security incidents, regulation, or provider decisions. An event-triggered extension could update when z falls below a threshold or when readiness exceeds a required level. Such an extension would connect the enterprise application more directly to event-triggered impulsive control research [34, 39]. Self-triggered impulsive control provides a complementary route when the next intervention time is determined from the state at the previous impulse rather than through continuous monitoring [40].

Third, the parameter values are normalized. Empirical calibration would require release logs, validation results, user-training data, process-mining measures, and incident records. A longitudinal case study could estimate the post-release drop in x, the recovery rate, and the relationship between adaptation measures and disruption.

Fourth, the model treats governance investment as a constant rate. In reality, firms may concentrate investment before a major update and reduce it afterward. An optimal-control extension could make $g(t)$ time-varying. A differential game could also represent strategic interaction between the enterprise and the model provider.

Fifth, the objective function is deliberately stylized. Different organizations will assign different weights to productivity, stability, risk, and update cost. Regulated or safety-critical processes may impose a hard minimum on $x(t)$ rather than a quadratic penalty. Future studies could formulate constrained optimization or risk-sensitive objectives.

Finally, the model does not explicitly represent stochastic model behavior. Random output variation, uncertain incidents, and unexpected provider changes could be incorporated through stochastic differential equations or random impulses. The deterministic framework developed here provides a baseline for those extensions.

8 Conclusion

Enterprise GenAI systems are updated repeatedly after adoption. These updates can raise technical effectiveness while disrupting workflows, invalidating employee knowledge, and increasing review burdens. Treating a release as a purely technical event therefore misses an important part of its enterprise impact.

This study developed an impulsive dynamical system in which process stability, organizational adaptation, and effective model capability evolve continuously between discrete updates. The analysis established positive invariance, the existence of a periodic operating trajectory, a closed-form periodic solution for effective model capability, and a spectral-radius condition for local stability. Numerical simulations showed that frequent small updates reduce disruption amplitude, whereas infrequent large updates create deeper short-term stability losses. Higher governance investment expands organizational adaptation and supports a more technically ambitious release policy. Cognitive overload has the opposite effect.

The optimization results indicate that neither maximum stability nor maximum update intensity is generally optimal. The best policy balances a moderate update interval, a moderate release intensity, and sufficient governance investment. The precise numerical optimum is conditional on the normalized calibration, but the structural result is broader: update interval, update intensity, and organizational adaptation should be managed jointly.

The central managerial message is that the unit of GenAI governance should be the complete release cycle. Enterprises should evaluate readiness before deployment, monitor minimum and average process stability after deployment, and treat training and process redesign as parts of the technical release. This approach can help organizations obtain the benefits of rapid model improvement without converting every improvement into a recurring operational shock.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The author declares no conflicts of interest.

AI Use Statement

The author declares that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable.

References

[1] Dumas, M., Fournier, F., Limonad, L., Marrella, A., Montali, M., Rehse, J. R., ... & Weber, I. (2023). AI-augmented business process management systems: a research manifesto. *ACM Transactions on Management Information Systems, 14*(1), 1-19. [CrossRef]

[2] Rosemann, M., Brocke, J. V., Van Looy, A., & Santoro, F. (2024). Business process management in the age of AI–three essential drifts. *Information Systems and e-Business Management*, *22*(3), 415-429. [CrossRef]

[3] Wornow, M., Narayan, A., Opsahl-Ong, K., McIntyre, Q., Shah, N. H., & Re, C. (2024). Automating the enterprise with foundation models. *arXiv preprint arXiv:2405.03710*. [CrossRef]

[4] Bommasani, R., Hudson, D. A., Adeli, E., Altman, R., Arora, S., von Arx, S., ... & Liang, P. (2021). On the opportunities and risks of foundation models. *arXiv preprint arXiv:2108.07258*. [CrossRef]

[5] Beheshti, A., Yang, J., Sheng, Q. Z., Benatallah, B., Casati, F., Dustdar, S., ... & Xue, S. (2023, July). ProcessGPT: transforming business process management with generative artificial intelligence. In *2023 IEEE international conference on web services* (*ICWS*) (pp. 731-739). IEEE. [CrossRef]

[6] Kampik, T., Warmuth, C., Rebmann, A., Agam, R., Egger, L. N., Gerber, A., ... & Weidlich, M. (2025). Large process models: a vision for business process management in the age of generative AI. *KI-Künstliche Intelligenz, 39*(2), 81-95. [CrossRef]

[7] Vidgof, M., Bachhofner, S., & Mendling, J. (2023, September). Large language models for business process management: Opportunities and challenges. In *International conference on business process management* (pp. 107-123). Cham: Springer Nature Switzerland. [CrossRef]

[8] Klievtsova, N., Benzin, J. V., Kampik, T., Mangler, J., & Rinderle-Ma, S. (2023, September). Conversational process modelling: state of the art, applications, and implications in practice. In *International conference on business process management* (pp. 319-336). Cham: Springer Nature Switzerland. [CrossRef]

[9] Kourani, H., Berti, A., Schuster, D., & Van der Aalst, W. M. (2025). Evaluating large language models on business process modeling: framework, benchmark, and self-improvement analysis. *Software and Systems Modeling*, 1-36. [CrossRef]

[10] Rana, N. P., Pillai, R., Sivathanu, B., & Malik, N. (2024). Assessing the nexus of Generative AI adoption, ethical considerations and organizational performance. *Technovation, 135*, 103064. [CrossRef]

[11] Yang, J., Blount, Y., & Amrollahi, A. (2024). Artificial intelligence adoption in a professional service industry: A multiple case study. *Technological Forecasting and Social Change, 201*, 123251. [CrossRef]

[12] Hughes, L., Davies, F., Li, K., Gunaratnege, S. M., Malik, T., & Dwivedi, Y. K. (2026). Beyond the hype: Organisational adoption of Generative AI through the lens of the TOE framework–A mixed methods perspective. *International journal of information management*, *86*, 102982. [CrossRef]

[13] Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. *Science, 381*(6654), 187-192. [CrossRef]

[14] Dell'Acqua, F., McFowland III, E., Mollick, E., Lifshitz, H., Kellogg, K. C., Rajendran, S., ... & Lakhani, K. R. (2026). Navigating the jagged technological frontier: Field experimental evidence of the effects of artificial intelligence on knowledge worker productivity and quality. *Organization Science, 37*(2), 403-423. [CrossRef]

[15] Röglinger, M., Plattfaut, R., Borghoff, V., Kerpedzhiev, G., Becker, J., Beverungen, D., ... & Trkman, P.

(2022). Exogenous shocks and business process management: a scholars' perspective on challenges and opportunities. *Business & Information Systems Engineering*, *64*(5), 669-687. [CrossRef]

[16] Zhu, H., Ji, X., & Lu, J. (2023). Impulsive strategies in nonlinear dynamical systems: A brief overview. *Mathematical Biosciences and Engineering*, *20*(2), 4274-4321. [CrossRef]

[17] Dashkovskiy, S., & Slynko, V. (2022). Stability conditions for impulsive dynamical systems. *Mathematics of Control, Signals, and Systems*, *34*(1), 95-128. [CrossRef]

[18] Liu, K. (2022). Stability analysis for (ω, c)-periodic non-instantaneous impulsive differential equations. *AIMS Mathematics*, *7*(2), 1758-1774. [CrossRef]

[19] Teubner, T., Flath, C. M., Weinhardt, C., van der Aalst, W., & Hinz, O. (2023). Welcome to the era of ChatGPT et al. *Business & Information Systems Engineering*, *65*(2), 95-101. [CrossRef]

[20] Chen, L., Zaharia, M., & Zou, J. (2023). How is ChatGPT's behavior changing over time? *arXiv preprint arXiv:2307.09009*. [CrossRef]

[21] Mariani, M., & Dwivedi, Y. K. (2024). Generative artificial intelligence in innovation management: A preview of future research developments. *Journal of Business Research*, *175*, 114542. [CrossRef]

[22] Brynjolfsson, E., Li, D., & Raymond, L. (2025). Generative AI at Work. *The Quarterly Journal of Economics*, *140*(2), 889-942. [CrossRef]

[23] Bouha, C., & Benhayoun, L. (2026). From Promise to Pressure: An Employee-Focused, Context-Aware Framework of AI Adoption Balancing Performance and Cognitive Load. *Knowledge and Process Management*. [CrossRef]

[24] Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of management review*, *46*(1), 192-210. [CrossRef]

[25] Jöhnk, J., Weißert, M., & Wyrtki, K. (2021). Ready or Not, AI Comes— An Interview Study of Organizational AI Readiness Factors. *Business & information systems engineering*, *63*(1), 5-20. [CrossRef]

[26] Kreuzberger, D., Kühl, N., & Hirschl, S. (2023). Machine learning operations (MLOps): Overview, definition, and architecture. *IEEE Access*, *11*, 31866-31879. [CrossRef]

[27] Amrit, C., & Narayanappa, A. K. (2025). An analysis of the challenges in the adoption of MLOps. *Journal of Innovation & Knowledge*, *10*(1), 100637. [CrossRef]

[28] Serban, A., van der Blom, K., Hoos, H., & Visser, J. (2024). Software engineering practices for machine learning—adoption, effects, and team assessment. *Journal of Systems and Software*, *209*, 111907. [CrossRef]

[29] Eck, B., Kabakci-Zorlu, D., Chen, Y., Savard, F., & Bao, X. (2022, December). A monitoring framework for deployed machine learning models with supply chain examples. In *2022 IEEE International Conference on Big Data (Big Data)* (pp. 2231-2238). IEEE. [CrossRef]

[30] Bayram, F., Ahmed, B. S., & Kassler, A. (2022). From concept drift to model degradation: An overview on performance-aware drift detectors. *Knowledge-Based Systems*, *245*, 108632. [CrossRef]

[31] Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., ... & Wright, R. (2023). Opinion Paper:"So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International journal of information management*, *71*, 102642. [CrossRef]

[32] Xu, H., Zhu, Q., & Zheng, W. X. (2023). Exponential stability of stochastic nonlinear delay systems subject to multiple periodic impulses. *IEEE Transactions on Automatic Control*, *69*(4), 2621-2628. [CrossRef]

[33] Li, X., Wang, Y., & Song, S. (2022). Stability of nonlinear impulsive systems: Self-triggered comparison system approach. *IEEE Transactions on Automatic Control*, *68*(8), 4940-4947. [CrossRef]

[34] Wang, M., Li, P., & Li, X. (2023). Event-triggered delayed impulsive control for input-to-state stability of nonlinear impulsive systems. *Nonlinear Analysis: Hybrid Systems*, *47*, 101277. [CrossRef]

[35] Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... & Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International journal of information management*, *57*, 101994. [CrossRef]

[36] Mäntymäki, M., Minkkinen, M., Birkstedt, T., & Viljanen, M. (2022). Putting AI ethics into practice: The hourglass model of organizational AI governance. *arXiv preprint arXiv:2206.00335*. [CrossRef]

[37] Mäntymäki, M., Minkkinen, M., Birkstedt, T., & Viljanen, M. (2022). Defining organizational AI governance. *AI and Ethics*, *2*(4), 603-609. [CrossRef]

[38] Fettke, P., & Di Francescomarino, C. (2025). KI-SI: Business Process Management (BPM) in the Era of AI (BPM-AI). *KI-Künstliche Intelligenz*, *39*(2), 63-65. [CrossRef]

[39] Zhang, K., & Braverman, E. (2022). Event-triggered impulsive control for nonlinear systems with actuation delays. *IEEE Transactions on Automatic Control*, *68*(1), 540-547. [CrossRef]

[40] Li, X., & Wang, M. (2024). Stability for nonlinear delay systems: Self-triggered impulsive control. *Automatica*, *160*, 111469. [CrossRef]