

Beyond Project Status: System Shift as a Structural Diagnostic Framework for Predicting Delay, Stagnation, and Adaptive Progression in Pharmaceutical Development Portfolios

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Keywords	Abstract
System Shift; pharmaceutical development; project stagnation; bottlenecks; organizational learning.	Project stagnation in pharmaceutical development portfolios is often recorded administratively but insufficiently diagnosed structurally. This study introduces and empirically examines System Shift as a structural diagnostic framework for reading delay, stagnation, adaptive progression, and success in pharmaceutical development portfolios. The framework operationalizes seven dimensions: System Condition, Domain Lock, Actor Complexity, Chokepoint Severity, Position Quality, Strategy Quality, and Feedback Maturity. The empirical setting is an exploratory, coded dataset of 41 project-level cases drawn from a broader portfolio of 112 pharmaceutical development projects. Results provide strong exploratory support for the framework. Chokepoint Severity showed a very strong association with Delay_Months ($r = 0.9318$; $R^2 = 0.8682$; slope = 1.8202), while Feedback Maturity and Strategy Quality positively predicted Success and Progression. The composite System_Shift_Risk_Score outperformed a status-only model in predicting Delay, Success, and Progression. Four visual analyses further strengthen the evidence: a correlation heatmap reveals a clear pressure-versus-adaptation architecture; a regression plot shows the functional relationship between chokepoints and delay; a feature-importance chart shows the comparative predictive salience of risk and feedback variables; and a cluster plot distinguishes low-risk adaptive, high-chokepoint stagnant, and transitional cases. The paper argues that System Shift offers an empirically promising diagnostic pathway for portfolio governance in complex pharmaceutical development systems. Because the sample is small, single-site, and first-pass coded, the study is best interpreted as exploratory empirical validation rather than final generalizable proof.

INTRODUCTION

The pharmaceutical industry has long faced a persistent productivity challenge in research and development, marked by rising development cost, high attrition, declining output efficiency, and the difficulty of translating scientific effort into successful development outcomes (Cook et al., 2014; Morgan et al., 2018; Paul et al., 2010; Pammolli et al., 2011). This concern has generated a large body of work on decision quality, portfolio governance, innovation portfolio management, and organizational learning in drug development and project-based organizations (Jekunen, 2014; Kock & Gemünden, 2016). Yet one practical problem remains undiagnosed: why do some development projects become structurally stuck even when they remain administratively visible, technically active, and formally reviewed?

In many development organizations, projects are classified by status labels such as lab trial, procurement, pilot scale, bioequivalence preparation, registration preparation, exhibit

batch, or hold. These labels are useful for coordination, but not for explanation. A project can be in a lab trial because it is progressing through expected experimentation, or because it is trapped in unresolved formulation, analytical, material, or equipment constraints (Kumar et al., 2020). A project can be on hold because of a clear strategic decision or because decision rights, technical evidence, and resource availability no longer align. In this sense, status tells the observer where the project is, but not why the project is unable to move.

The empirical setting motivating this paper is a pharmaceutical development portfolio comprising 112 pipeline projects as of May 2026, including 78 new-product-development cases and 34 existing-product-improvement cases. The portfolio profile shows a heavy concentration in Lab Trial, with additional concentrations in Hold, Exhibit Batch, Procurement, Queuing, Pilot BE Study, Done T0, and Devpro Preparation. Such a pattern suggests a portfolio that is not merely large but structurally congested. It also shows why a conventional status dashboard may be insufficient: the portfolio requires not only tracking but also diagnosis.

The same portfolio material contains concrete examples of technical and coordination constraints. An injectable 1% infusion project showed dissolved-oxygen issues, capping mismatch, and visible-particle rejection. Several solid oncology projects were affected by dissolution similarity issues, comparator availability, BE failures, API source decisions, assay issues, and supplier warnings. Parenteral-nutrition projects incompletely exhibited analytical-method dependencies, raw-material verification gaps, unfinished equipment qualification, and costly analytical logistics. These examples are not isolated anecdotes. They are empirical signals of a system in which movement depends on the interaction between technical constraints, coordination density, resource access, and learning capacity.

This concern has been addressed through work on pharmaceutical R&D productivity, portfolio decision quality, innovation portfolio governance, and organizational learning across project-based settings (Jekunen, 2014; Kock & Gemünden, 2016).

This paper proposes System Shift as a structural diagnostic framework for reading such conditions, building on the author's broader work on systems in motion, pharmaceutical political economy, and AI-enabled decision architecture in pharmacy and organizational transformation (Tjandrawinata, 2026a; Tjandrawinata, 2026b; Tjandrawinata, 2026c). Its central proposition is that project delay and stagnation emerge from the interaction between pressure-side variables and adaptive-side variables. The pressure side consists of System Condition, Domain Lock, Actor Complexity, and Chokepoint Severity. The adaptive side consists of Position Quality, Strategy Quality, and Feedback Maturity (Verschueren et al., 2023). The framework does not assume that delay is caused by a single actor or a single decision. Instead, it treats delay as a system-state phenomenon: movement becomes difficult when structural pressure accumulates faster than the system's capacity to position, respond, learn, and reconfigure (Akyol et al., 2026; Kumar et al., 2020; Verschueren et al., 2023).

The urgency of this research is underscored by the substantial economic and public health implications of pharmaceutical development delays. With development costs exceeding \$2 billion per drug and attrition rates remaining high, the ability to diagnose and address stagnation early is critical for improving R&D productivity and accelerating patient access to therapies (Chuang-Stein & Kirby, 2021; Subbiah et al., 2024). The novelty of this paper lies in its introduction of a middle-range diagnostic framework that operationalizes seven dimensions of structural pressure and adaptive response capacity, providing exploratory empirical validation

using 41 coded project-level cases. This study aims to demonstrate that System Shift has meaningful criterion-related and predictive validity as an exploratory diagnostic model, offering a complement to existing productivity and portfolio frameworks by addressing the problem of structural stagnation inside development portfolios after projects are already in motion.

Project stagnation, bottlenecks, and chokepoints

The closest established analog to the System Shift concept of Chokepoint Severity is bottleneck theory, where constraining nodes exert disproportionate influence on the performance of the entire production or organizational network. In production and operational systems, bottlenecks are constraining nodes that slow the performance of the entire chain. Their importance lies not only in the existence of delay, but in the disproportionate effect that a localized constraint can exert on whole-system performance. In portfolio settings, the same logic becomes more complex because bottlenecks can arise in technical work, analytical readiness, material flow, equipment access, regulatory preparation, vendor dependency, cross-functional decision timing, and the interdependence among multiple concurrent projects (Martinsuo, 2013).

Project stagnation should therefore be distinguished from ordinary delay. Ordinary delay may reflect a temporary deviation from the schedule; stagnation reflects an impairment of movement between system states. A project may still generate meetings, reports, samples, or trials, yet remain structurally unable to transition to the next stage of development. The System Shift framework adopts this distinction by treating Chokepoint Severity as the intensity of the active constraint that blocks movement, rather than merely the presence of a task delay.

Complex adaptive systems and portfolio behavior

Complex adaptive systems theory provides a broader conceptual framework for understanding why portfolios do not behave like simple aggregates of independent projects, because outcomes emerge from interaction, adaptation, feedback, and distributed learning among multiple agents. Development portfolios consist of interacting projects, teams, sites, vendors, technical methods, analytical platforms, regulatory expectations, and resource constraints. Their outcomes emerge from distributed interaction, feedback, and adaptation rather than from linear control alone.

This perspective is essential in multi-project environments, where complexity grows through interdependence rather than through the simple addition of separate projects. When a portfolio grows in scale, complexity does not increase merely by addition. It increases through interdependence: one method-development delay can affect multiple projects; one material dependency can slow several cases; one regulatory interpretation can change the priority of an entire group of products. System Shift is not proposed as a general theory of complexity. It is proposed as a diagnostic architecture that makes complexity scorable, comparable, and actionable in portfolio governance.

Organizational learning and feedback maturity

The organizational-learning literature is also central to System Shift because development portfolios repeatedly generate signals from failed trials, assay deviations, supplier delays, bioequivalence outcomes, method-transfer problems, regulatory questions, and post-trial observations, yet signals become learning only when they are captured, interpreted, codified, and translated into corrective action (Carrillo et al., 2013). Development portfolios

generate repeated signals: failed trials, assay deviations, supplier delays, BE outcomes, method-transfer problems, regulatory questions, and post-trial observations. However, the presence of signals does not guarantee learning. Learning requires that signals be captured, interpreted, translated into corrective action, and then fed back into future decisions.

Feedback Maturity is therefore not equivalent to reporting frequency; it refers to the system's ability to convert experience into adaptive correction across project, team, and organizational levels (Wiewiora et al., 2019). A system can produce many reports and still fail to learn. In the System Shift framework, feedback maturity refers to the strength of iterative use, correction, and adaptation of evidence. A mature feedback loop shortens the distance between deviation and correction. It enables the system to decide whether a problem requires technical optimization, escalation, reprioritization, reallocation, or structural redesign.

Project and innovation portfolio management

Project and innovation portfolio management scholarship has long emphasized selection, prioritization, resource allocation, strategic alignment, and decision quality as core mechanisms of portfolio performance. More recent work also stresses agility, contextual practice, and the limits of purely rational portfolio models, especially under uncertainty, technical constraint, and changing organizational conditions (Martinsuo, 2013; Kock & Gemünden, 2016). This shift is important because portfolio governance is not simply a mathematical allocation problem. It is a real-time diagnostic problem under uncertainty, technical constraints, and organizational learning pressure.

Pharmaceutical development intensifies the diagnostic problem because projects move through staged evidence generation, technical qualification, regulatory expectations, and cumulative path dependence. A weak early interpretation of technical or analytical difficulty can later manifest as delays, failures, or portfolio congestion. System Shift contributes to portfolio management by focusing less on whether a project should be selected and more on why a selected project stall (Jekunen, 2014).

System Shift components

The System Shift framework comprises seven coded dimensions. The first four represent structural pressure; the last three represent adaptive response capacity.

1. **System Condition:** Baseline system pressure and uncertainty surrounding the project.
2. **Domain Lock:** The degree to which the project is structurally locked into a method, supplier, technical pathway, instrument, site, or legacy process.
3. **Actor Complexity:** The density of actors, functions, vendors, units, and decision nodes involved in project movement.
4. **Chokepoint Severity:** The intensity of the active bottleneck blocking transition from one development state to another.
5. **Position Quality:** The quality of the project team's understanding of its leverage position within the system.
6. **Strategy Quality:** The extent to which the intervention addresses the actual constraint rather than generating superficial activity.
7. **Feedback Maturity:** The strength of iterative evidence uses, correction, and learning across project cycles.

3. Research Questions and Hypotheses

1. RQ1. Does Chokepoint Severity predict delay and stagnation in pharmaceutical development cases?
2. RQ2. Do Feedback Maturity and Strategy Quality predict progression and success?
3. RQ3. Does the System_Shift_Risk_Score outperform a status-only model in predicting delay, progression, and success?
4. RQ4. Do the cases cluster into theoretically meaningful adaptive, stagnant, and transitional profiles?
5. H1. Chokepoint Severity is positively associated with Delay_Months.
6. H2. Chokepoint Severity is positively associated with stagnation and negatively associated with Progression and Success.
7. H3. Feedback Maturity is positively associated with Success.
8. H4. Feedback Maturity is positively associated with Progression.
9. H5. Strategy Quality is positively associated with Success and Progression.
10. H6. The composite System_Shift_Risk_Score predicts Delay_Months, Success, and Progression better than status alone.
11. H7. Cluster analysis yields interpretable profiles corresponding to low-risk adaptive, high-risk stagnant, and transitional cases.

METHOD

Research design and empirical setting

The study used an exploratory empirical-methodological design. It is exploratory because the coding architecture is newly proposed, the sample is limited, and the data come from a single organizational setting. It is empirical because the framework is tested against observable project outcomes rather than defended only conceptually. It is methodological because the main contribution is the development and early validation of a diagnostic measurement architecture.

The empirical setting is an internal pharmaceutical development portfolio update dated May 2026. The source material documents a 112-project pipeline with substantial concentrations in Lab Trial, Hold, Procurement, Exhibit Batch, Queuing, Pilot BE Study, Done T0, and Devpro Preparation. From this broader portfolio, 41 project-level cases with sufficient descriptive evidence were coded into the pilot validation dataset. The analytic file included SC, DL, AC, CP, POS, STR, FB, System_Shift_Risk_Score, Weighted_Risk_Score, Delay_Months, Progression, Success, and Outcome_Status.

Coding rubric and variables

Each System Shift component was scored on a 1-5 diagnostic scale. Outcome variables were Delay_Months, Progression (0/1), Success (0/1), and Outcome_Status. The coding was based on available slide evidence and is therefore treated as a first-pass diagnostic coding appropriate for exploratory validation, not as a final audited dataset. This treatment is consistent with early-stage construct validation, where conceptual clarity, indicator specification, and alignment between the construct and its measurement model are more important than premature claims of final measurement certainty (MacKenzie et al., 2011). All coding was performed by a single coder; inter-rater reliability assessment is planned for future validation phases.

Table 1. Coding architecture for the seven System Shift components

Component	Definition	Scale anchor	Expected sign if framework is valid
System Condition	Baseline system pressure and uncertainty	1 = stable; 5 = very high pressure	Positive delay/stagnation with
Domain Lock	Degree of structural lock-in	1 = flexible; 5 = locked	Positive delay/stagnation with
Actor Complexity	Coordination and actor density	1 = simple; 5 = complex	Positive delay/stagnation with
Chokepoint Severity	Intensity of active bottleneck	1 = minor; 5 = critical stop	Strongest positive predictor of delay/stagnation
Position Quality	Strategic positioning in relation to the system	1 = reactive; 5 = anticipatory	Negative with delay; positive with success
Strategy Quality	Quality of response or intervention	1 = weak; 5 = directly addresses chokepoint	Negative with delay; positive with success
Feedback Maturity	Strength of iterative learning and correction	1 = absent; 5 = mature evidence-driven loop	Negative with delay; positive with success

The primary composite index was defined as:

$$\text{System_Shift_Risk_Score} = \text{SC} + \text{DL} + \text{AC} + \text{CP} - \text{POS} - \text{STR} - \text{FB}$$

Statistical analysis plan

The empirical testing strategy began with descriptive statistics and correlation analysis, followed by criterion-related and predictive validation tests. The analysis included simple linear regression of CP on Delay_Months, simple linear regression of CP on Stagnation where Stagnation = 1 - Progression, logistic models using FB and STR to predict Success and Progression, comparison of the System_Shift_Risk_Score model against a status-only model, feature-importance inspection, and three-cluster analysis.

A formal EFA/CFA/SEM test was not treated as decisive in this version because the sample size is small and the framework is better understood at this stage as a diagnostic composite architecture rather than a reflective latent-variable model requiring full factor-analytic confirmation (Wolf et al., 2013). The sample size is small, several predictors are strongly correlated, and, at this stage, the framework is better understood as a diagnostic composite architecture rather than a reflective latent-variable model. Given the small single-site sample and strong intercorrelations among several predictors, the present study prioritizes exploratory criterion validity, predictive comparison, and state-based clustering over formal latent-variable confirmation, since multicollinearity and correlated predictor structures may distort coefficient interpretation and variable-importance estimates.

RESULTS AND DISCUSSION

Descriptive statistics

The descriptive profile of the sample indicates a portfolio under meaningful strain but not total collapse. Mean values were SC = 3.439, DL = 3.317, AC = 3.659, CP = 3.463, POS = 3.171, STR = 3.463, FB = 2.585, Delay_Months = 3.244, Progression = 0.488, and Success = 0.390. This configuration is analytically favorable for exploratory validation because it contains enough variation to distinguish stalled, slowly moving, progressing, and successful cases.

Table 2. Descriptive statistics for the coded dataset

Variable	Mean	SD	Min	Max
SC	3.439	1.097	2.000	5.000
DL	3.317	1.128	2.000	5.000
AC	3.659	0.728	3.000	5.000
CP	3.463	1.120	2.000	5.000
POS	3.171	0.803	2.000	4.000
STR	3.463	0.596	2.000	4.000
FB	2.585	0.741	1.000	4.000
System_Shift_Risk_Score	4.659	5.606	-3.000	14.000
Delay_Months	3.244	2.188	1.000	8.000
Progression	0.488	0.506	0.000	1.000
Success	0.390	0.494	0.000	1.000

Correlation structure

The correlation structure strongly supports the theoretical architecture. On the pressure side, CP was strongly associated with Delay_Months ($r = 0.932$) and negatively associated with Progression ($r = -0.806$) and Success ($r = -0.742$). On the adaptive side, FB correlated negatively with Delay_Months ($r = -0.769$) and positively with Progression ($r = 0.820$) and Success ($r = 0.727$). STR showed the same directional pattern with Delay_Months ($r = -0.645$), Progression ($r = 0.724$), and Success ($r = 0.730$). The aggregate System_Shift_Risk_Score was even stronger, correlating 0.954 with Delay_Months, -0.856 with Progression, and -0.790 with Success.

Figure 1 visualizes the full correlation structure of the System Shift variables and outcomes. A clear two-pole pattern is evident. The pressure-side variables, namely System Condition, Domain Lock, Actor Complexity, and Chokepoint Severity, move together and are positively associated with Delay_Months and the composite System_Shift_Risk_Score. By contrast, the adaptive-side variables, namely Position Quality, Strategy Quality, and Feedback Maturity, move in the opposite direction and align positively with Progression and Success. This pattern is theoretically consistent with the framework's central proposition that project stagnation arises from the interaction between structural pressure and adaptive response capacity. At the same time, the high correlations among several pressure-side predictors require methodological caution: the current study supports exploratory criterion validity more strongly than independent latent-dimensional validation.

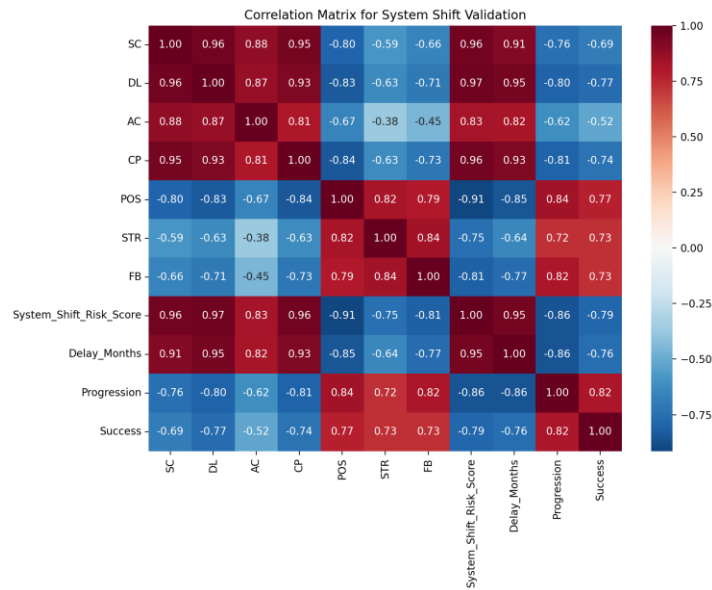


Figure 1. Correlation matrix for the System Shift validation sample

The figure shows strong positive associations among pressure-side variables (SC, DL, AC, CP, and System_Shift_Risk_Score), inverse associations between pressure-side and adaptive-side variables (POS, STR, FB), and the expected alignment of adaptive-side variables with Progression and Success.

Table 3. Key correlations between System Shift variables and outcomes

Predictor	Delay_Months	Progression	Success
SC	0.913	-0.756	-0.694
DL	0.950	-0.803	-0.766
AC	0.820	-0.622	-0.524
CP	0.932	-0.806	-0.742
POS	-0.849	0.836	0.773
STR	-0.645	0.724	0.730
FB	-0.769	0.820	0.727
System_Shift_Risk_Score	0.954	-0.856	-0.790

Linear regression of delay and stagnation

The strongest empirical result is the simple linear model of CP predicting Delay_Months. The model produced slope = 1.8202, intercept = -3.0603, $R^2 = 0.8682$, Pearson $r = 0.9318$, and p approximately 0. Interpreted substantively, each one-point increase in Chokepoint Severity was associated with approximately 1.82 additional months of delay. For an exploratory organizational dataset, this is a very large effect and gives direct support to the proposition that active chokepoints are central engines of delay.

Figure 2 depicts the relationship between Chokepoint Severity and Delay_Months. The fitted line and the relatively narrow spread around it provide visual support for the strong bivariate association. In substantive terms, the figure makes the paper's core claim visible: delay in this portfolio is not random administrative drift, but is concentrated around the severity of active bottlenecks. The corresponding stagnation model was also strong. With Stagnation defined as 1 - Progression, the CP to Stagnation regression yielded slope = 0.3639, intercept =

-0.7483, $R^2 = 0.6490$, Pearson $r = 0.8056$, and p approximately 0. This indicates that chokepoints do not merely lengthen project duration; they also alter the movement state of the system by increasing the probability that the project becomes functionally stuck.

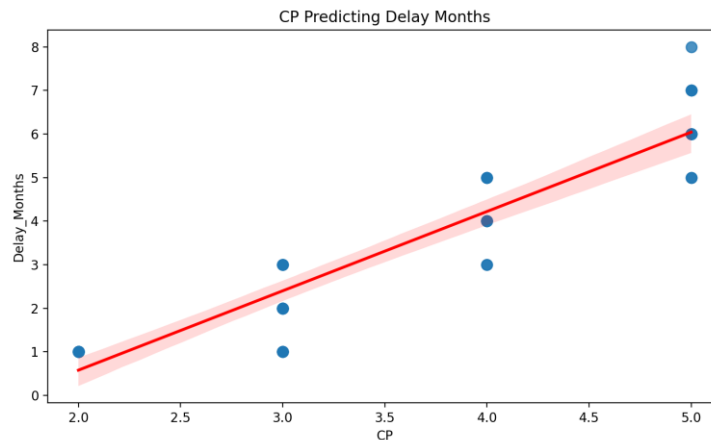


Figure 2. Chokepoint Severity predicting Delay_Months

The scatterplot with fitted regression line shows a strong positive relationship between active bottleneck severity and project delay. The figure visually supports the reported regression result that higher chokepoint severity is associated with longer delay.

Table 4. Linear regression results for delay and stagnation

Model	Slope	Intercept	r	R ²	p-value
CP -> Delay_Months	1.8202	-3.0603	0.9318	0.8682	~0
CP -> Stagnation	0.3639	-0.7483	0.8056	0.6490	~0

Logistic models for success and progression

The adaptive side of the framework is also supported. In the logistic model predicting Success, the coefficients were FB = 1.6833 and STR = 1.6163, with apparent accuracy = 0.9024 and log loss = 0.2863. Exponentiating these coefficients gives approximate odds ratios of 5.38 for FB and 5.03 for STR. Within the limits of an exploratory model, this indicates that stronger feedback maturity and strategy quality were associated with substantially higher odds of success.

The Progression model is even more revealing. The coefficients were FB = 2.3026 and STR = 1.0696, with apparent accuracy = 0.9512 and log loss = 0.2424. Translated into odds ratios, these coefficients imply approximately 10.00 for FB and 2.91 for STR. The theoretical implication is important: feedback maturity appears even more decisive for keeping projects moving than for producing success per se. This supports the interpretation of feedback as the key adaptive mechanism rather than a secondary management variable.

Table 5. Logistic regression results for Success and Progression

Outcome	Predictor	Coefficient	Approx. odds ratio	Apparent accuracy	Log loss
Success	FB	1.6833	5.38	0.9024	0.2863
Success	STR	1.6163	5.03	0.9024	0.2863
Progression	FB	2.3026	10.00	0.9512	0.2424
Progression	STR	1.0696	2.91	0.9512	0.2424

Comparative model performance and feature importance

One of the most important validation tests is whether the System Shift composite adds value beyond conventional status labels. For Delay_Months, the risk-score model achieved $R^2 = 0.9111$, whereas the status-only model achieved $R^2 = 0.7074$. For Success, the risk-score model achieved $AUC = 0.9700$ compared with $AUC = 0.9575$ for status alone. For Progression, the comparison was $AUC = 0.9869$ for the risk-score model versus 0.9762 for the status-only model. This is one of the clearest arguments for the manuscript’s novelty: System Shift is not merely a relabeling of existing project status categories; it appears to provide incremental diagnostic validity.

Figure 3 summarizes feature importance across Delay, Success, and Progression. The dominant role of System_Shift_Risk_Score is visually clear, especially for Delay, while Feedback Maturity emerges as particularly consequential for Progression. This pattern reinforces the interpretation that cumulative structural risk explains delay most strongly, whereas adaptive learning capacity is critical for maintaining movement through the portfolio. However, the feature-importance results should be read as exploratory rather than definitive, because the predictors are strongly correlated. Under correlated-predictor conditions, variable-importance rankings can be unstable or difficult to interpret without additional robustness checks, particularly when predictors share overlapping structural information within a small exploratory dataset.

Table 6. Model comparison between System Shift risk score and status-only model

Outcome	System Shift model	Status-only model	Better model
Delay_Months	$R^2 = 0.9111$	$R^2 = 0.7074$	System Shift
Success	$AUC = 0.9700$	$AUC = 0.9575$	System Shift
Progression	$AUC = 0.9869$	$AUC = 0.9762$	System Shift

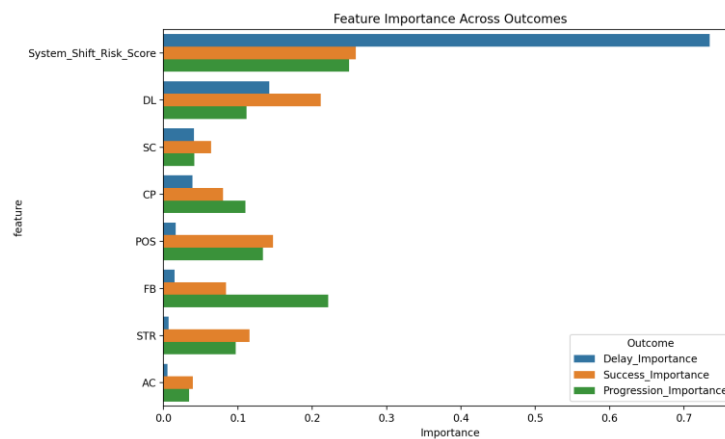


Figure 3. Feature importance across Delay, Success, and Progression

The chart shows that System_Shift_Risk_Score is the most prominent predictor overall, especially for Delay, while Feedback Maturity becomes comparatively more important for Progression. Because several predictors are highly correlated, these feature-importance estimates should be interpreted as exploratory model-inspection results.

Table 7. Feature importance across outcomes

Feature	Delay importance	Success importance	Progression importance
System_Shift_Risk_Score	0.7345	0.2586	0.2497
DL	0.1424	0.2116	0.1118
SC	lower	lower	lower
CP	lower	0.0800	0.1101
POS	lower	0.1472	0.1338
FB	lower	0.0842	0.2216
STR	lower	0.1154	0.0970
AC	lower	lower	lower

Risk score and cluster structure

The risk score is also substantively meaningful as a portfolio discriminator. In the coded dataset, the score ranges from -3 to 14, with a mean of 4.659. That spread is useful because it separates relatively adaptive and structurally risky cases within the same portfolio. A diagnostic score is valuable only if it can stratify cases into different operating conditions; here, the System_Shift_Risk_Score does precisely that.

Cluster analysis produced three highly interpretable groups. Cluster 0 contained 17 cases with CP = 2.412, POS = 4.000, STR = 4.000, FB = 3.235, Risk Score = -1.000, Delay_Months = 1.176, Progression = 1.000, and Success = 0.882; this is the adaptive low-risk cluster. Cluster 1 contained 18 cases with CP = 4.556, POS = 2.444, STR = 3.111, FB = 2.056, Risk Score = 10.222, Delay_Months = 5.389, Progression = 0.056, and Success = 0.056; this is clearly the high-chokepoint stagnant cluster. Cluster 2 contained 6 cases with CP = 3.167, POS = 3.000, STR = 3.000, FB = 2.333, Risk Score = 4.000, Delay_Months = 2.667, Progression = 0.333, and Success = 0.000; this is the transitional cluster.

Figure 4 integrates risk score, delay, cluster membership, and success marking in one display. The cases separate into three structurally meaningful regions rather than forming a single undifferentiated cloud. Low-risk cases occupy the lower-left region and coincide with lower delay and more favorable outcomes; high-risk cases concentrate in the upper-right region and align with long delay and failure; transitional cases occupy the middle zone. This state-based visualization strengthens the framework’s theoretical claim that portfolios contain adaptive, stagnant, and transitional conditions rather than merely binary outcomes.

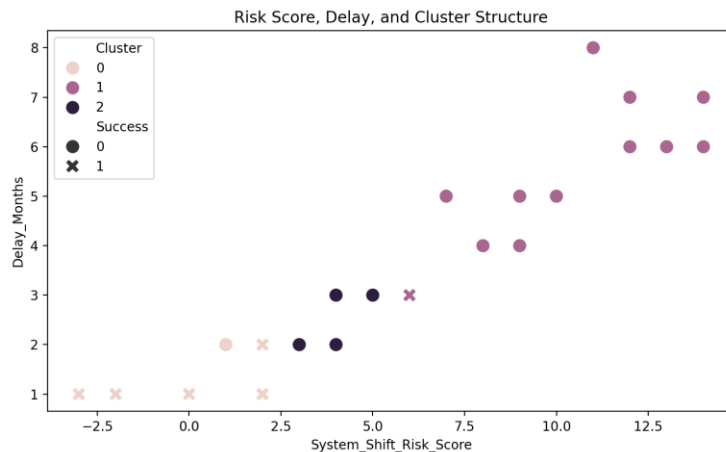


Figure 4. Risk score, delay, and cluster structure

Cases separate into low-risk adaptive, high-risk stagnant, and intermediate transitional regions. Marker shape indicates success, while color denotes cluster membership. The figure visually supports the argument that System Shift distinguishes structural states of portfolio movement rather than only success/failure outcomes.

Table 8. Cluster centroids from the exploratory analysis

Cluster	n	CP	POS	STR	FB	Risk Score	Delay_Months	Progression	Success	Interpretation
0	1	2.41	4.00	4.00	3.23	-	1.176	1.000	0.882	Low-risk adaptive
	7	2	0	0	5	1.000				
1	1	4.55	2.44	3.11	2.05	10.22	5.389	0.056	0.056	High-chokepoint stagnant
	8	6	4	1	6	2				
2	6	3.16	3.00	3.00	2.33	4.000	2.667	0.333	0.000	Transitional
	7	0	0	3						

The first major finding is that chokepoints are structural rather than incidental. The empirical strength of the CP-to-Delay_Months relationship suggests that project stagnation in this portfolio is not well understood as generic delay noise. It is better understood as a system being held by one or more active constraints. This interpretation is reinforced by source examples from infusion, oncology, and parenteral nutrition projects, where the observed problems were specific technical, analytical, material, or coordination blockages rather than abstract management labels.

The second major finding is that feedback is the operative mechanism of adaptive movement. Feedback Maturity was strongly associated with both Success and Progression, and was particularly powerful for Progression. In practical terms, Strategy Quality matters, but its effect is amplified when the system can monitor what happens, detect mismatches quickly, and revise action. This supports the view that learning is not a peripheral process in development portfolios. It is a core movement mechanism.

The third major finding is that the System_Shift_Risk_Score adds diagnostic value beyond status-only labeling. This is the manuscript's most important publishing argument. Administrative classifiers are useful but limited. The present results make that limitation observable: the risk-based model systematically outperformed a simpler status model. System Shift therefore operationalizes a deeper structural concern: a portfolio must be read not only by location in the process, but by the configuration of pressure, lock-in, chokepoints, position, strategy, and feedback.

The fourth major finding is that the case set naturally divides into adaptive, stagnant, and transitional regimes. This moves the framework beyond linear regression into system-state diagnosis. In portfolio-governance terms, different states imply different interventions. Adaptive cases should be protected and accelerated. Stagnant cases require chokepoint removal, re-scoping, or escalation. Transitional cases require intensified feedback and strategic redesign before they drift into the stagnant regime.

The paper contributes to pharmaceutical management scholarship by offering a diagnostic complement to existing productivity and portfolio frameworks. Much of the pharmaceutical R&D literature emphasizes disciplined decision criteria, scientific quality, candidate selection, and portfolio prioritization. System Shift addresses a different but related

problem: how to diagnose structural stagnation inside a development portfolio after projects are already in motion.

Practical and Managerial Implications

For portfolio leaders, the practical implication is direct: project review should move beyond status reporting toward structural diagnosis. Instead of asking only whether a project is in lab trial, procurement, pilot scale, or hold, the portfolio review should ask what the active chokepoint is, whether it is technical, material, analytical, regulatory, resource-based, or coordination-based, and whether the current intervention actually touches that chokepoint.

The System Shift score can also support triage. Cases with low risk and strong feedback can be accelerated. Cases with high chokepoint severity and weak feedback need immediate structural intervention. Transitional cases are particularly important because they may still be recoverable. In those cases, better feedback loops and targeted strategy may prevent drift into long-term stagnation.

The framework can therefore function as a portfolio diagnostic dashboard, a training tool for cross-functional teams, and a governance mechanism for escalation. Its value lies not in replacing expert judgment, but in making expert judgment more systematic, comparable, and auditable.

Limitations and Future Research

The study has important limitations. First, the sample consists of 41 coded cases, which is adequate for exploratory pilot validation but not for universal validation. Second, the empirical context is a single organization, which means the results may reflect both the strength of the framework and the specific structure of the portfolio. Third, the coding is first-pass and was not yet subjected to formal multi-rater reliability assessment. Fourth, several pressure-side variables are strongly correlated, so diagnostic coherence is high but independent-parameter interpretation is less secure. Fifth, the study uses apparent model performance and exploratory feature-importance inspection, both of which require larger external validation samples before stronger claims can be made.

These limitations define the next research agenda. Future studies should include independent multi-rater coding, inter-rater reliability testing, cross-unit or cross-firm replication, longitudinal follow-up, and larger samples suitable for EFA/CFA/SEM, because sample size, construct specification, model propriety, and measurement validity are central requirements for stronger validation of diagnostic frameworks (MacKenzie et al., 2011; Wolf et al., 2013). The strongest next test would be prospective: score projects at time t and assess whether high-risk cases show greater realized delay, lower phase transition, or lower success at time $t + 6$ months or time $t + 12$ months. Future work should also compare System Shift against existing stage-gate dashboards, portfolio risk matrices, and project-status classifications to assess incremental predictive validity under more rigorous conditions.

CONCLUSION

This study provides strong exploratory empirical support for the System Shift framework as a structural diagnostic model for pharmaceutical development portfolios. Chokepoint Severity is the dominant predictor of delay and stagnation; Feedback Maturity and Strategy Quality support progression and success; and the composite System_Shift_Risk_Score outperforms a status-only model. The four integrated figures clarify the evidence visually: the

heatmap reveals the pressure-versus-adaptation architecture, the regression plot shows chokepoints driving delay, the feature-importance chart shows the salience of risk score and feedback, and the cluster plot demonstrates that the portfolio contains adaptive, stagnant, and transitional states. The appropriate claim is therefore disciplined but strong: System Shift is not yet universally validated, but it is empirically supported as an exploratory structural diagnostic framework with criterion-related and predictive validity in this pharmaceutical development portfolio. The next scholarly step is not to expand the claim rhetorically, but to deepen the evidence through multi-rater scoring, longitudinal validation, and cross-organizational replication.

REFERENCES

- Akyol, H. B., Preist, C., & Schien, D. (2026). Investigating temporal delays in time-series forecasts: Detection and quantification with the n-step-shifting method. *IEEE Access*.
- Carrillo, P., Ruikar, K., & Fuller, P. (2013). When will we learn? Improving lessons learned practice in construction. *International Journal of Project Management*, 31(4), 567–578.
- Chuang-Stein, C., & Kirby, S. (2021). *Quantitative decisions in drug development*. Springer.
- Cook, D., Brown, D., Alexander, R., March, R., Morgan, P., Satterthwaite, G., & Pangalos, M. N. (2014). Lessons learned from the fate of AstraZeneca's drug pipeline. *Nature Reviews Drug Discovery*, 13(6), 419–431.
- Jekunen, A. (2014). Decision-making in product portfolios of pharmaceutical research and development: Managing streams of innovation in highly regulated markets. *Drug Design, Development and Therapy*, 8, 2009–2016.
- Kock, A., & Gemünden, H. G. (2016). Antecedents to decision-making quality and agility in innovation portfolio management. *Journal of Product Innovation Management*, 33(6), 670–686.
- Kumar, S. T., Donzelli, S., Chiki, A., Syed, M. M. K., & Lashuel, H. A. (2020). A simple, versatile and robust centrifugation-based filtration protocol for the isolation and quantification of α -synuclein monomers, oligomers and fibrils: Towards improving experimental reproducibility in α -synuclein research. *Journal of Neurochemistry*, 153(1), 103–119.
- MacKenzie, S. B., Podsakoff, P. M., & Podsakoff, N. P. (2011). Construct measurement and validation procedures in MIS and behavioral research: Integrating new and existing techniques. *MIS Quarterly*, 35(2), 293–334.
- Martinsuo, M. (2013). Project portfolio management in practice and in context. *International Journal of Project Management*, 31(6), 794–803.
- Morgan, P., Brown, D. G., Lennard, S., Anderton, M. J., Barrett, J. C., Eriksson, U., Fidock, M., Hamrén, B., Johnson, A., March, R. E., Matcham, J., Mettetal, J., Nicholls, D. J., Platz, S., Rees, S., Snowden, M. A., & Pangalos, M. N. (2018). Impact of a five-dimensional framework on R&D productivity at AstraZeneca. *Nature Reviews Drug Discovery*, 17(3), 167–181.
- Pammolli, F., Magazzini, L., & Riccaboni, M. (2011). The productivity crisis in pharmaceutical R&D. *Nature Reviews Drug Discovery*, 10(6), 428–438.
- Paul, S. M., Mytelka, D. S., Dunwiddie, C. T., Persinger, C. C., Munos, B. H., Lindborg, S. R., & Schacht, A. L. (2010). How to improve R&D productivity: The pharmaceutical industry's grand challenge. *Nature Reviews Drug Discovery*, 9(3), 203–214.
- Subbiah, V., Burris III, H. A., & Kurzrock, R. (2024). Revolutionizing cancer drug development: Harnessing the potential of basket trials. *Cancer*, 130(2), 186–200.
- Tjandrawinata, R. R. (2026a). *System shift: Membaca dunia sebagai struktur dalam gerak*.

- Rajawali Press. (In press).
- Tjandrawinata, R. R. (2026b). *Ekonomi politik sistem farmasi global: Interdependensi, risiko dan kegagalan kontinuitas*. Rajawali Press. (In press).
- Tjandrawinata, R. R. (2026c). *Artificial intelligence pharmacy: Arsitektur keputusan dan transformasi sistem*. Rajawali Press. (In press).
- Verschueren, N., Van Dessel, J., Verslyppe, A., Schoensetters, Y., & Baelmans, M. (2023). A maturity matrix model to strengthen the quality cultures in higher education. *Education Sciences, 13*(2), 123.
- Wiewiora, A., Smidt, M., & Chang, A. (2019). The "how" of multilevel learning dynamics: A systematic literature review exploring how mechanisms bridge learning between individuals, teams/projects and the organization. *European Management Review, 16*(1), 93–115.
- Wolf, E. J., Harrington, K. M., Clark, S. L., & Miller, M. W. (2013). Sample size requirements for structural equation models: An evaluation of power, bias, and solution propriety. *Educational and Psychological Measurement, 73*(6), 913–934.