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AI-ENABLED QUALITY-BY-DESIGN WORKFLOW FOR TABLET COMPRESSION USING SPECTRAL, GRANULE, AND PROCESS DATA

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ABSTRACT

Tablet compression is a critical manufacturing step in which raw materials, granule attributes, and process settings converge to determine the quality of the final solid dosage form. Compression behavior influences mechanical strength, dissolution, content uniformity, and manufacturability. Traditional Quality-by-Design workflows often rely on univariate interpretation, static multivariate models, or limited design-of-experiments outputs. This leaves unrealized value in the rich spectral, granule, and process datasets now generated by modern manufacturing systems. This article proposes an AI-enabled QbD workflow that integrates NIR and Raman spectral data, granule physical properties, and tablet press parameters into a unified predictive and optimization framework. The aim is to support conceptual design-space development, process understanding, and real-time quality decision-making. The proposed workflow uses data fusion to align spectral, granule, and compression data into model-ready representations. Gradient-boosted models, neural networks, and chemometric baselines are positioned as complementary tools for predicting hardness, dissolution, and content uniformity within a lifecycle-oriented QbD structure.
Conceptually, the workflow could identify suitable compression settings for each granule batch, anticipate quality deviations, and support adaptive model maintenance as new manufacturing data become available. It would be expected to transform fragmented PAT measurements into a coherent quality intelligence layer. An AI-enhanced QbD workflow could accelerate tablet process development, reduce avoidable batch failures, and strengthen the scientific basis for real-time release testing. Its value depends on transparent model governance, validated analytical data, and practical integration with manufacturing control systems.

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Introduction

Tablet compression is a pivotal operation in solid dosage manufacturing because it converts powders or granules into a dosage form whose mechanical and biopharmaceutical performance must remain within narrow quality limits. Studies of tableting control have shown that compression behavior can be modeled from process variables and material states, making the compression step a logical focus for predictive control [1]. Forward-control concepts developed for tableting [2] further illustrate that compression quality is not only a function of target force but also of upstream variability, press dynamics, and the evolving state of the material bed.

The introduction of Process Analytical Technology and Quality-by-Design has expanded the quantity and diversity of data available during solid dosage development and manufacture. Continuous manufacturing case studies have demonstrated how PAT can connect blending, feeding, and tableting information to support process understanding [3], while spectroscopic monitoring in tableting lines has shown how chemical and physical signals can be captured during production [4]. However, the ability to collect NIR, Raman, terahertz, and process historian data has often advanced faster than the ability to integrate those data into actionable QbD decisions.

Artificial intelligence offers a pathway to move from isolated data analysis toward dynamic, multivariate process understanding. Spectroscopy-based dissolution prediction using neural networks [5] and fast dissolution-profile modeling from spectral data [6] show that machine learning can represent relationships that are difficult to capture with simple linear

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assumptions. Real-time release models that incorporate NIR spectra, compression force, and particle size information [7] suggest that AI can unify material, process, and product-quality information into a single decision framework.
This article develops a conceptual AI-enabled QbD workflow that consumes spectral, granule, and tablet compression data and converts them into a validated, adaptable control strategy. Raman mapping and imaging-based dissolution prediction studies [8, 9] indicate that spatially resolved product information can complement process signals, while multivariate models linking formulation, process, and spectroscopic measurements to dissolution behavior [10] support a broader systems view. The proposed AIF is therefore positioned as a workflow architecture rather than an experimental report, emphasizing how existing PAT and AI capabilities could be organized into a coherent QbD lifecycle.

Background

Quality-by-Design and Process Analytical Technology Fundamentals

Quality-by-Design begins with the quality target product profile and critical quality attributes, then links these outputs to critical material attributes and critical process parameters through structured risk assessment and design-space development. PAT strengthens this framework by enabling in-line or at-line measurement of blend uniformity, content, density, and other process-relevant states, as demonstrated in continuous manufacturing and commercial product monitoring studies [3, 11]. Real-time quantification of low-dose formulations within flowing powder systems [12, 13] further illustrates how PAT can support the scientific basis for real-time release by reducing reliance on delayed end-product testing.

Spectral Data for Tablet Process Monitoring

Spectral data from NIR, Raman, UV/VIS imaging, and terahertz platforms can provide chemical and physical information relevant to blend quality, tablet structure, and downstream performance. NIR sampling interfaces have been used to estimate low drug concentration and powder-state properties inside feed-frame environments [14], while Raman spectroscopic monitoring has been connected to feedback control in continuous blending and tableting [15]. Terahertz measurements have also been applied to non-destructive assessment of tablet disintegration and dissolution behavior [16, 17], showing that spectral PAT can extend beyond assay into structural and performance-relevant attributes.

Granule Properties Influencing Tablet Compression

Granule properties such as particle size distribution, bulk density, moisture content, and flowability affect die filling, compressibility, compactibility, and ejection behavior during tablet manufacture. PAT platforms designed to predict granule tableting properties [18] support the view that upstream material characterization can inform downstream compression decisions before a batch reaches the press. Machine learning studies that connect material-library descriptors to tablet properties [19] and powder physical properties to multiple tablet quality attributes [20] further indicate that granule and powder features should be treated as core inputs in an AI-enabled QbD workflow.

Machine Learning in Pharmaceutical Process Modeling

Machine learning in pharmaceutical process modeling can complement chemometrics by representing non-linear relationships between formulation, material attributes, process parameters, and product quality. Retrospective QbD studies using interpretable neural networks [21] demonstrate how developmental data can be reorganized into process knowledge, while explainable recurrent neural networks for tableting batch analysis [22] suggest that temporal process histories can be evaluated in a manner compatible with Pharma 4.0 expectations. Ultrasonic and machine-learning approaches to tablet quality assessment [23] also show that AI can integrate non-traditional signals into real-time release concepts.

Data Fusion and Holistic Process Understanding

Data fusion provides a formal strategy for combining heterogeneous data blocks, including spectra, physical granule descriptors, process parameters, and quality measurements. Reviews of data fusion in PAT describe low-level, mid-level, and high-level approaches that can be selected according to data structure, interpretability needs, and model risk [24]. Practical data-fusion studies using multiple PAT instruments [25] support the idea that fused representations can provide a more complete process view than any single sensor or measurement modality.

Workflow Overview

High-Level QbD Workflow

The proposed workflow begins with acquisition of spectral, granule, and compression process data, then proceeds through preprocessing, temporal alignment, data fusion, predictive model development, design-space construction, control deployment, and model monitoring. Continuous manufacturing studies using PAT [3] and process-specific tableting control models [1, 2] provide the conceptual foundation for treating compression as a data-rich decision point rather than a fixed unit operation. In this AIF, the model does not replace QbD judgment; instead, it organizes experimental, process, and analytical evidence into a transparent workflow that could support science-based control decisions.
Figure 1 illustrates the proposed AI-enabled Quality-by-Design workflow that converts spectral, granule, tablet press, and laboratory quality data into predictive design-space intelligence, real-time control support, and lifecycle model governance for tablet compression.

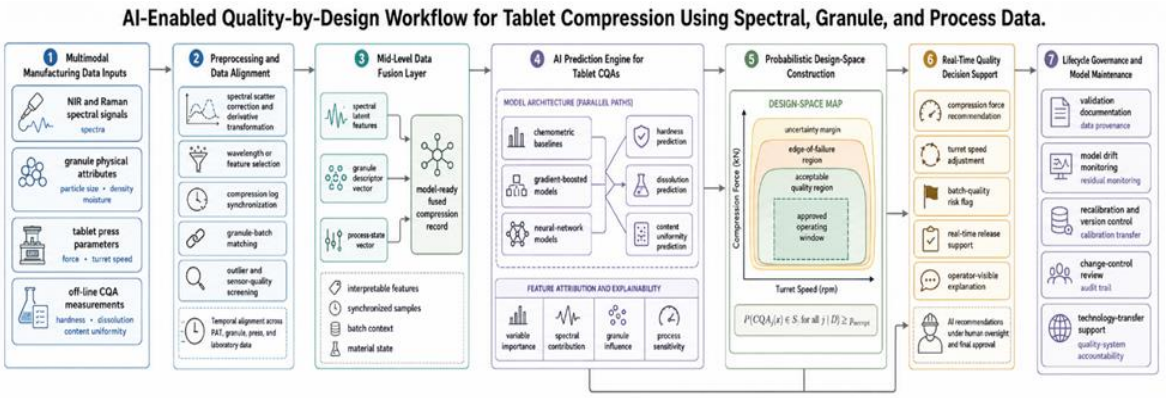

Figure 1. AI-Enabled Quality-by-Design Workflow for Tablet Compression Using Spectral, Granule, and Process Data

Core Input Data Streams

The core input streams include NIR or Raman spectra from blends or tablets, granule descriptors such as particle size and density, tablet press parameters such as force and speed, and off-line CQA measurements such as hardness, dissolution, and assay. Real-time dissolution modeling from NIR spectra, compression force, and particle size distribution [7] directly supports this multimodal input structure. Additional imaging and spectroscopic approaches for crushing strength, drug content, particle size inspection, and API content [26-28] show how product-quality labels and sensor-derived features could be connected within the same supervised-learning framework.

Design Principles

The workflow should be modular, scalable, explainable, and compatible with regulatory expectations for lifecycle management and real-time release. Robust control strategies for bilayer tablets have already combined QbD, statistical methods, and PAT concepts [29], suggesting that AI should be embedded within established pharmaceutical quality systems rather than treated as an isolated digital layer. Large-scale comparisons of batch and continuous tablet manufacturing [30] also indicate that the workflow should support technology choices across manufacturing modes and remain adaptable during development, scale-up, and transfer.

Data Sources and Data Fusion Strategy

Acquisition and Pre-Processing of Spectral, Granule, and Process Data

Spectral preprocessing would include scatter correction, derivative transformation, wavelength selection, and outlier screening before spectra are linked to granule and compression records. NIR-based methods for low-dose powder monitoring [12-14] show why preprocessing and sampling context are critical when spectral responses are influenced by density, flow, and composition. Compression log data should then be aligned to tablet sampling events, while granule batch averages and distributional descriptors should be structured so that each fused record reflects the material state entering the press [18, 20]. **Figure 2** illustrates how raw PAT, granule, tablet press, and CQA data are converted into synchronized, model-ready evidence units for AI-enabled QbD decision-making.

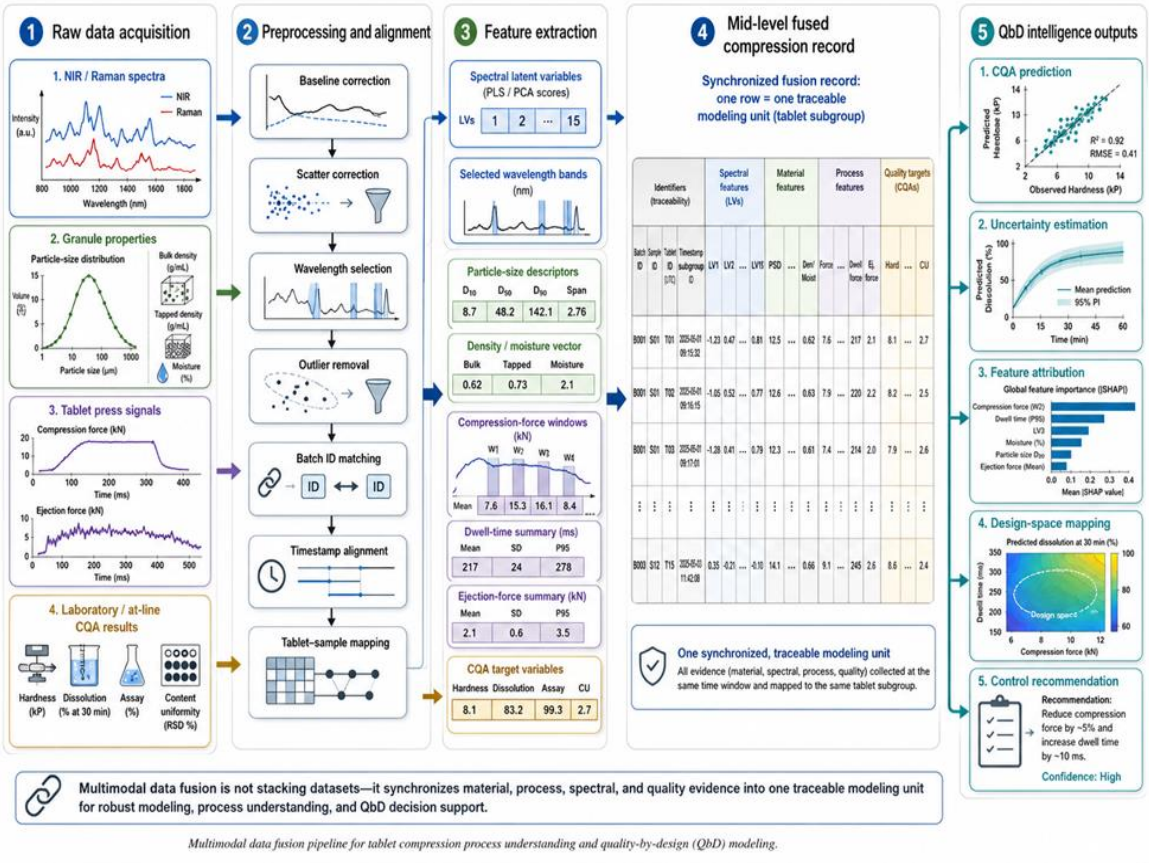

Figure 2. Multimodal Data Fusion Pipeline for AI-Enabled Tablet Compression QbD

Mid-Level Data Fusion

Mid-level data fusion would extract compact, interpretable features from each data block before combining them into a single modeling vector. For example, spectral scores could be derived from NIR or Raman data, granule features could summarize particle size and density, and process variables could represent the compression state near each sampling event, consistent with broader PAT data-fusion strategies [24]. Studies using multiple PAT instruments [25] and combined NIR, compression force, and particle size inputs for real-time release modeling [7] support this mid-level architecture because it balances predictive richness with model interpretability.

Table 1 maps each data stream in the proposed workflow to its pharmaceutical meaning, AI-ready representation, CQA relevance, and QbD decision function.

Table 1. Multimodal Input-to-Decision Architecture for an AI-Enabled QbD Tablet Compression Workflow

Workflow Component	Representative Data Elements	Pharmaceutical Meaning	AI-Ready Representation	CQA Linkage	QbD Decision Function
Spectral PAT signals	NIR spectra, Raman spectra, wavelength bands, spectral scores, probe location metadata	Captures chemical composition, blend uniformity, API distribution, and physical-state variation during manufacturing	Preprocessed spectral features, latent scores, selected bands, spectral-distance measures	Dissolution, content uniformity, assay, blend/tablet composition	Supports real-time quality surveillance and detection of chemical or physical deviations before final testing
Granule material attributes	Particle size distribution, bulk density, tapped density, flowability, moisture content, compressibility indicators	Represents the upstream material state entering compression and explains batch-to-batch tableting behavior	Batch-level descriptors, distribution summaries, material fingerprints, normalized granule vectors	Hardness, friability, dissolution, die filling consistency, ejection behavior	Enables feed-forward adjustment of compression settings according to incoming material variability
Tablet press process parameters	Compression force, pre-compression force, turret speed, feeder speed, dwell time, punch displacement, ejection force	Represents the mechanical conditions that convert granules into tablets with target structural and performance attributes	Time-aligned process windows, event-level summaries, process-state vectors, temporal trajectories	Hardness, weight variation, tensile strength, capping risk, dissolution behavior	Defines controllable CPPs and supports adaptive process operation within a validated design space

Laboratory and at-line CQA labels	Hardness, dissolution profile, content uniformity, assay, disintegration, friability	Provides validated product-quality outcomes required for supervised learning and model verification	Target variables, specification classes, continuous CQA labels, pass/fail quality indicators	All critical product-quality attributes	Anchors model predictions in pharmaceutically meaningful and analytically validated quality endpoints
Fused compression record	Linked spectral, granule, process, and CQA observations	Represents the integrated material–process–product relationship for each batch, sample, or tablet subgroup	Mid-level fused feature vector with batch and sampling context	Multi-CQA prediction and joint quality-risk estimation	Converts fragmented PAT and process data into an integrated QbD evidence unit
Predictive model outputs	Predicted hardness, dissolution, content uniformity, uncertainty estimates, residuals	Estimates whether current or proposed compression conditions will produce acceptable tablet quality	Model predictions, prediction intervals, calibrated risk scores, residual diagnostics	Anticipated CQA compliance or deviation	Supports design-space mapping, process recommendation, real-time release justification, and deviation prevention
Interpretability outputs	Feature importance, spectral contribution, granule influence, process sensitivity, residual explanation	Explains which material or process variables drive predicted quality outcomes	SHAP-style attribution, partial-dependence summaries, sensitivity ranking, process-context narratives	Identifies dominant drivers of CQA variability	Translates AI predictions into quality-risk knowledge compatible with QbD reasoning
Lifecycle monitoring signals	Drift indicators, spectral-distance checks, prediction error trends, calibration status, version logs	Determines whether the model remains valid as materials, sensors, sites, or equipment change	Monitoring dashboards are avoided; instead use statistical control summaries, residual charts, and model-governance records	Sustained prediction reliability across batches and sites	Triggers review, recalibration, retraining, or change-control action when the validated domain is exceeded

Quality Attribute Measurements and Target Definition

The fused feature vectors require validated quality labels that represent tablet hardness, dissolution, content uniformity, or related CQAs. Spectroscopy-based and imaging-based studies have connected non-destructive measurements to dissolution, crushing strength, drug content, and particle size outcomes [5, 6, 26], providing examples of how analytical targets can be defined for supervised learning. Transmission Raman and NIR hyperspectral imaging for content uniformity assessment [31] further indicate that model labels should be grounded in robust analytical methods and linked carefully to the physical sample represented by each fused data record.

AI-Driven Modeling and Prediction Engine

Predictive Modeling of Tablet CQAs

The prediction engine would use a committee of complementary models, such as chemometric baselines, tree-based learners, gradient-boosted models, and neural networks, to estimate tablet hardness, dissolution, and content uniformity from fused data. Neural-network dissolution prediction [5, 6], formulation-process-spectroscopy dissolution modeling [10], and material-to-tablet property modeling [19] show how different model families can contribute to CQA prediction. Weighted model averaging or Bayesian stacking could then be evaluated conceptually as a way to combine interpretable baseline behavior with flexible non-linear learning while preserving the QbD requirement for scientific justification.

Probabilistic Design Space Definition

The AI model would support probabilistic design-space definition by attaching uncertainty estimates to predicted CQAs and identifying regions of process operation where quality would be expected to remain acceptable. Interpretable neural networks for retrospective QbD [21] and explainable recurrent models for tableting batch analysis [22] suggest that model outputs should be accompanied by feature attribution, residual review, and process-context interpretation. Non-destructive terahertz and optical methods for dissolution and hardness assessment [16, 17, 32] could also provide additional evidence streams for judging whether the predicted design space remains physically meaningful.

Real-Time Feed-Back Control Concept

The real-time control concept would connect the predictive model to a supervisory layer that recommends or adjusts compression force, turret speed, or related settings when incoming data suggest movement toward the edge of the validated design space. Forward-control modeling in tableting [1, 2] and Raman-based monitoring with feedback control in continuous powder blending and tableting [15] provide conceptual precedents for converting PAT measurements into process actions. In the proposed workflow, AI recommendations should be constrained by pre-approved control logic, operator visibility, and model-monitoring rules so that automation strengthens rather than obscures pharmaceutical quality decision-making.

QbD Integration – Design Space and Control Strategy

Mapping the Process Design Space with AI

The AI-enabled design space would be represented as a non-linear map linking granule properties, spectral signatures, and compression parameters to predicted tablet CQAs. Prior work on feed-forward tableting control [1, 2] supports the idea that compression settings can be adapted to material state, while real-time release models using NIR spectra, compression force, and particle size distribution [7] show how spectral, process, and material data can be combined for design-space reasoning. A conceptual acceptance rule for a candidate operating condition (x) could be expressed $s\,P\big(\,CQA_j(x) \in S_j\;\forall j \mid D\,\big) \geq paccept$, where (D) denotes the fused development and manufacturing data, (S_j) denotes the approved specification region for each CQA, and p_{accept} denotes the pre-defined quality-confidence requirement.

Risk-Based Control Strategy Development

A risk-based control strategy would use model interpretation to identify which variables most strongly influence hardness, dissolution, assay, or content uniformity. Interpretable neural-network approaches for retrospective QbD [21] and explainable recurrent models for tableting process analysis [22] support the use of feature attribution to connect AI outputs with familiar quality-risk tools. In practice, variables such as granule moisture, particle size distribution, compression force, feeder behavior, or spectral deviations would be prioritized for control when the model indicates that they are influential and practically measurable [18, 20].

Regulatory-Friendly Model Documentation

Regulatory-friendly documentation should describe the intended model use, data provenance, preprocessing steps, model structure, validation logic, change-control plan, and drift-monitoring strategy. QbD and PAT case studies in continuous and bilayer tablet manufacturing [3, 29] show that model outputs must be embedded in a broader control strategy rather than presented as stand-alone predictions. The AI workflow should therefore generate traceable summaries of training data, feature importance, uncertainty handling, and human oversight so that regulators and site quality teams can understand how the model supports product quality decisions.

Model Monitoring, Maintenance, and Drift Handling

Continuous Model Performance Monitoring

Continuous model monitoring would compare new-batch predictions against subsequent laboratory or at-line quality measurements and examine residual patterns for evidence of process drift. Low-dose powder monitoring studies [12, 13] illustrate how sensor and sampling behavior can affect model reliability, while PAT applications in continuous manufacturing [3, 4] show that process context is essential when interpreting changing signals. Residual charts, spectral-distance checks, and material-fingerprint comparisons would therefore be expected to trigger model review when new observations no longer resemble the validated operating domain.

Figure 3 presents the lifecycle governance structure required to keep an AI-enabled compression model valid, traceable, and scientifically justified after deployment.

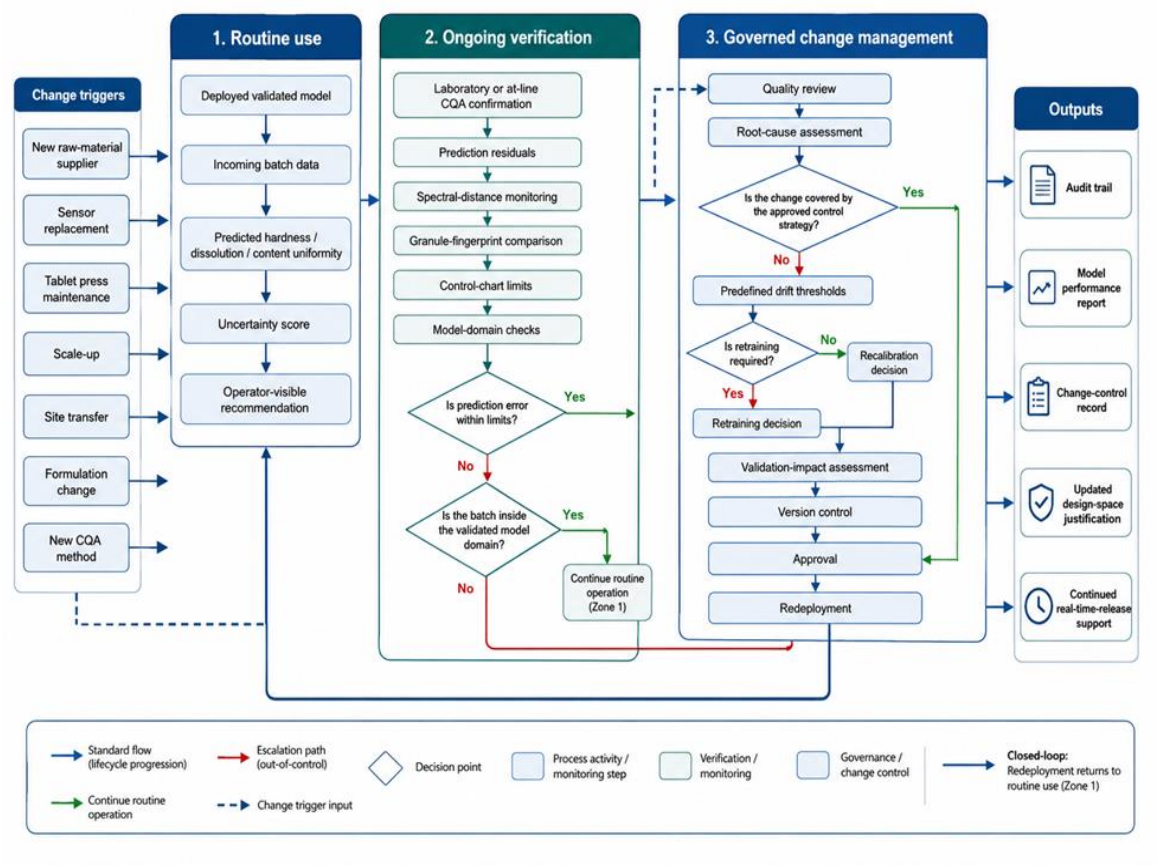

Figure 3. Lifecycle Governance Framework for AI Models in Tablet Compression QbD

Model Update and Lifecycle Management

Model maintenance should follow a lifecycle approach in which retraining, recalibration, and version control are governed by documented scientific justification. Data-fusion guidance in PAT [24] and practical fusion studies across multiple analytical instruments [25] suggest that changes in one data block, such as a new spectral probe or altered granule test method, can affect the full model pipeline. The workflow should therefore preserve previously validated knowledge while allowing controlled updates when new raw materials, sites, equipment, or process histories expand the evidence base [30].

Implementation and Technology Transfer Pathways

Integration with Manufacturing Execution Systems

Implementation would require the AI workflow to exchange data with manufacturing execution systems, process historians, tablet press control systems, and laboratory information systems. Raman-based monitoring and feedback control in continuous blending and tableting [15] shows how spectroscopic data can be connected to process action, while commercial continuous manufacturing PAT studies [3] demonstrate the need for robust integration between analytical systems and production infrastructure. Operators should receive model outputs as interpretable quality states and recommended control actions rather than opaque algorithmic scores.

Facilitating Technology Transfer

Technology transfer would be supported by representing process knowledge as a transparent data-driven design space rather than as a fixed set of site-specific settings. Comparisons of batch and continuous tablet manufacturing [30] indicate that process understanding must remain meaningful across manufacturing configurations, while material-library modeling [19] suggests that raw-material fingerprints can be used to anticipate differences in tableting behavior. The receiving site could therefore compare its spectral, granule, and process signatures with the approved design space and propose justified parameter adjustments before routine production begins.

Evaluation Strategy

Predictive Performance of CQA Models

Evaluation of CQA models should examine whether predictions for hardness, dissolution, and content uniformity are scientifically consistent, stable across batches, and useful for decision-making. Dissolution modeling from spectral and process data [5-7, 10] provides a basis for evaluating whether fused models capture relevant product-performance behavior, while content-uniformity studies using transmission Raman and NIR hyperspectral imaging [31] show how analytical reference

quality affects supervised-learning targets. Metrics such as prediction error, bias, and calibration behavior may be used internally, but interpretation should focus on whether the model is reliable enough to support the proposed QbD decision.

Design Space Reliability and Control Strategy Effectiveness

Design-space reliability should be evaluated by comparing AI-defined operating regions with prior scientific knowledge, process capability, and observed product quality. Optical, UV/VIS, and terahertz approaches for predicting hardness, dissolution, content, and structural performance [16, 17, 26–28, 31] can provide independent or complementary evidence that the selected design space is physically plausible. Control effectiveness should then be assessed conceptually by determining whether model-guided recommendations would keep the process within approved operating conditions while maintaining operator oversight and quality-system accountability [1, 15].

Workflow Efficiency and Regulatory Outcomes

Workflow efficiency should be evaluated by how well the AI-enabled QbD system organizes development knowledge, reduces redundant experimentation, and supports timely quality decisions. Retrospective QbD modeling [21], explainable batch analysis [22], and robust PAT-driven control strategy development [29] indicate that AI can convert accumulated development and manufacturing records into structured process understanding. Regulatory outcomes should be assessed through the clarity of model documentation, the defensibility of the design space, the adequacy of model-maintenance plans, and the ability to explain how predictions support real-time release decisions [3, 24].

Table 2 consolidates how the proposed AI-enabled workflow strengthens design-space definition, real-time control support, regulatory documentation, and lifecycle maintenance in tablet compression.

Table 2. Design-Space, Control, and Governance Functions of the Proposed AI-Enabled Tablet Compression QbD Workflow

QbD Function	Conventional Limitation Addressed	AI-Enabled Enhancement	Required Evidence or Documentation	Implementation Risk	Practical Control Implication
CQA prediction	Traditional models may evaluate hardness, dissolution, or content uniformity separately and may miss nonlinear relationships among material, process, and spectral variables	Multimodal models estimate multiple tablet CQAs from fused spectral, granule, and compression data	Model-development report, training dataset description, preprocessing record, validation against laboratory CQA results	Poor analytical labels or weak sample alignment can generate misleading predictions	Enables earlier detection of batches likely to deviate from target quality before final product testing
Probabilistic design-space mapping	Static design spaces may rely heavily on limited DoE conditions and may not reflect incoming batch variability	AI models attach uncertainty to predicted CQA outcomes and identify operating regions with acceptable quality confidence	Design-space justification, uncertainty-calibration assessment, comparison with prior process knowledge, acceptance-threshold rationale	Overconfident models may define design regions that are not physically or statistically defensible	Supports selection of compression settings that remain inside a quality-confidence boundary
Feed-forward compression adjustment	Fixed press settings may not account for differences in granule moisture, particle size, density, or flow behavior	Incoming material fingerprints inform compression force, speed, or feeder-related recommendations before routine compression	Material-characterization protocol, adjustment logic, operator review rules, approved parameter limits	Excessive automation may obscure the role of expert process judgment	Allows scientifically justified parameter adaptation while preserving operator oversight
Real-time release support	End-product testing may delay quality decisions and may not fully use PAT and process-history data	AI integrates PAT signals, compression logs, and validated CQA models to support real-time quality assessment	RTRT rationale, prediction-performance evidence, model traceability, analytical-method validation, quality-unit approval pathway	Regulatory acceptance may be limited if model logic and failure modes are not transparent	Provides a defensible bridge between process monitoring and release-oriented quality decisions
Explainability and quality-risk interpretation	Black-box predictions may be difficult to connect to established QbD tools such as CMA–CPP–CQA linkage and risk ranking	Feature attribution and sensitivity analysis identify influential spectral, material, and process drivers	Feature-importance records, scientific interpretation summaries, variable-control rationale, risk-assessment updates	Explanations may be technically correct but pharmaceutically meaningless if not reviewed by domain experts	Converts model outputs into actionable process understanding and control-priority ranking
Drift monitoring and	A model validated during development may degrade	Residual monitoring, spectral-distance checks,	Drift thresholds, monitoring frequency,	Frequent model updates may create validation	Defines when to continue using,

model maintenance	after raw-material, sensor, site, or equipment changes	and material-fingerprint comparison identify movement outside the validated domain	retraining criteria, version-control records, change-control procedures	burden and operational uncertainty	recalibrate, retrain, or retire the model
Technology transfer	Process knowledge may be transferred as fixed parameters rather than as an adaptable understanding of material–process–quality relationships	The fused design-space model allows receiving sites to compare local material and process signatures with the approved knowledge base	Site-comparison report, calibration-transfer evidence, equipment equivalence assessment, local verification batches	Site-specific sensor or equipment differences may reduce model portability	Supports justified parameter adaptation during transfer without losing QbD traceability
Regulatory and quality-system governance	AI tools may be treated as isolated digital solutions rather than controlled elements of the pharmaceutical quality system	Model documentation, audit trails, intended-use definition, human oversight, and change control embed AI within lifecycle QbD governance	Intended-use statement, model-risk classification, data-provenance record, validation package, governance SOPs	Incomplete documentation may prevent the model from supporting regulated decisions	Positions the AI workflow as a controlled quality-support system rather than an informal prediction tool

Limitations

Reliance on Input Data Quality

The workflow depends strongly on the quality, representativeness, and synchronization of spectral, granule, process, and laboratory data. Spectral monitoring studies in feed-frame and flowing-powder environments [12-14] show that sampling geometry, density variation, and powder movement can influence measurement reliability, while data-fusion reviews [24] emphasize that poor-quality blocks can compromise the fused model. Robust sensor maintenance, calibration transfer, outlier handling, and data-governance procedures are therefore prerequisites for any AI-enabled compression control strategy.

Initial Development Effort and Model Complexity

A multimodal AI-enabled QbD workflow would require substantial initial effort in data infrastructure, cross-functional expertise, validation planning, and quality-system integration. Studies combining spectroscopy, process variables, imaging, and machine-learning models [5-10, 26-28] demonstrate the breadth of technical knowledge required to build and maintain such systems. Smaller manufacturers may face barriers related to instrumentation, data engineering, and AI governance, so implementation should begin with well-scoped use cases before expanding toward closed-loop control.

Conclusion

The proposed AI-enabled QbD workflow fuses spectral, granule, and compression data into a predictive quality hub for tablet manufacturing. It reframes tablet compression as a dynamic, data-rich process in which material attributes, process settings, and product-quality measurements can be interpreted together.

The main strength of the workflow is its ability to support holistic process understanding, automated design-space refinement, and real-time quality decision-making. By combining PAT data with transparent AI models, the framework could help align development knowledge, manufacturing control, and real-time release objectives.

Important challenges remain before such workflows can become routine in commercial solid dosage manufacturing. These include data integration complexity, model lifecycle governance, workforce upskilling, sensor reliability, and the need to demonstrate that AI-supported decisions remain scientifically interpretable and quality-system compliant.

Industry, academia, technology providers, and regulators should collaborate on representative case studies using real tablet products and realistic manufacturing constraints. Such partnerships could establish practical expectations for AI-enhanced QbD and create regulatory precedent for adaptive, data-driven control strategies in solid dosage manufacturing.

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