



Scale-Up in Mineral Processing: From Mechanism Preservation to Flowsheet-Scale Transferability—A Critical Review and the MINESCALE Framework

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ABSTRACT

Scale-up in mineral processing is often reduced to equipment enlargement or empirical factors, although industrial performance emerges from coupled mechanisms whose relative importance changes with scale, continuity, inventory, recycle, ore variability, and control complexity. This structured critical narrative review synthesizes 144 contemporary sources published between 2020 and 2026 and draws on six foundational works to anchor canonical scale-up theory. The review covers comminution, classification, gravity and magnetic separation, flotation, solid–liquid separation, material handling, slurry transport, digital models, and integrated flowsheets. Evidence is interpreted through a mechanism-preservation perspective: laboratory performance is transferable only when the state variables controlling breakage, particle trajectories, hydrodynamics, residence-time distribution, rheology, interfacial phenomena, energy dissipation, segregation, and control dynamics are preserved, reproduced, or explicitly represented in an independently validated model. Ore variability is treated as the first scale-up boundary, followed by continuity and circuit integration. Quantitative cross-scale evidence shows that flotation batch-to-plant factors vary with particle size and liberation; classifier changes can alter throughput and specific grinding energy; and a continuous mini-pilot flowsheet at Kamoakakula closely predicted industrial copper recovery after commissioning. We propose the MINESCALE framework, comprising eight decision gates: feed representativeness, dominant mechanism, similarity criteria, variability, pilot relevance, model validation, flowsheet integration, and industrial transferability. Retrospective stress testing against selected published cross-scale cases suggests that the framework can distinguish among successful experiments, externally validated equipment models, and more transferable integrated design bases. Scale-up is therefore better treated as an auditable evidence-transfer problem than as size-based extrapolation.

Keywords: Mineral processing; Scale-up; Transferability; Process modeling; Ore variability; Industrial validation

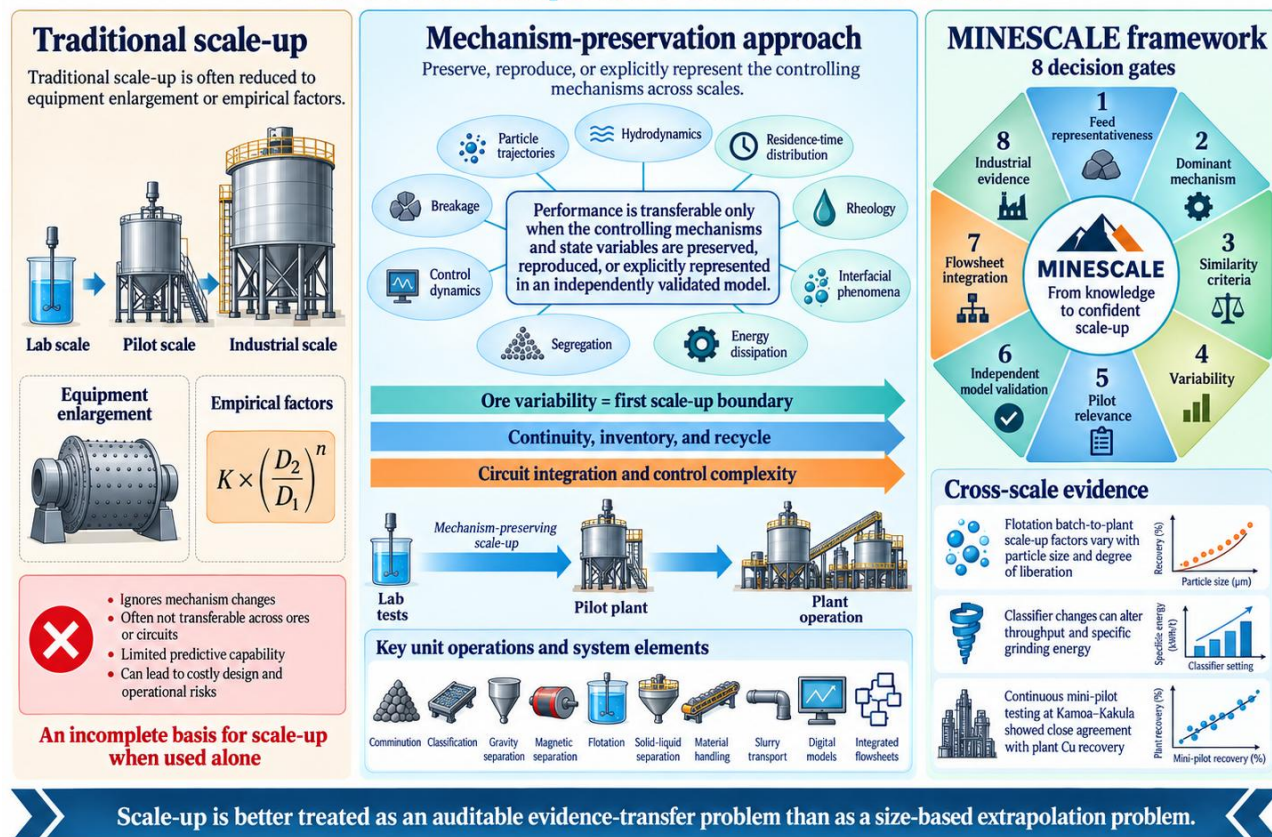
Highlights

- Scale-up validity depends on mechanism preservation, not equipment size alone.
- Ore variability is the first boundary for laboratory-to-industrial transferability.
- Unit-operation validity does not guarantee flowsheet-scale validity when recycles and disturbances are active.
- MINESCALE converts scale-up into eight auditable evidence gates from feed definition to industrial validation.

Graphical abstract

Scale-up in Mineral Processing

From size-based extrapolation to auditable evidence transfer



Structured critical narrative review: 144 contemporary sources (2020–2026) + 6 foundational works

1. INTRODUCTION

Mineral-processing projects routinely transform grams or kilograms of laboratory material into circuits that process hundreds to thousands of tonnes per hour. The engineering risk in this transition is not simply that industrial equipment is geometrically larger. The more consequential risk is that the mechanisms that drive laboratory performance change in importance as scale, residence time, inventory, hydrodynamics, recycle, feed heterogeneity, and control structure change. Direct pilot-to-industrial comparisons in SAG milling and flotation show that geometric similarity, nominal residence time, or a single empirical factor cannot guarantee transferability, while reactor–separator cells and digital grinding models reach the same conclusion from different mechanistic directions (Cleary et al., 2023; Contreras, 2025; Hassanzadeh & Hoang, 2026; Iveson et al., 2022; Yianatos et al., 2022; Yianatos & Vallejos, 2024).

The practical consequence is that scale-up error propagates beyond a single machine. An under-predicted circulating load can alter mill residence time, liberation, and power draw; an altered classification curve changes the feed presented to downstream separation; a change in froth recovery can invalidate a kinetic extrapolation; and water-recycle decisions can change surface chemistry throughout the plant. Commissioning evidence and systems-level reviews therefore increasingly treat the concentrator as a coupled dynamic system rather than a collection of independently sized units (Göktaş et al., 2023; Lotter et al., 2024; Mi et al., 2026; Moraga et al., 2022; Wepener et al., 2021; Witecki et al., 2022).

Recent literature provides unusually strong cross-scale evidence for this argument. Small and mini-pilot flotation devices reveal where hydrodynamics and transport diverge from plant-scale cells; industrial-scale HIGMill, HPGR, and jaw-crusher studies show the value of calibration against plant surveys; and commissioning campaigns demonstrate that the quality of the evidence pathway matters as much as the nominal scale reached (Awatey et al., 2026; de Jong, 2024; Hassanzadeh et al., 2024; Massinaei & Javanshiri,



2026; Rodriguez et al., 2026; Vasconcelos et al., 2026). At Kamoakakula, for example, a continuous mini-pilot mass and value balance predicted 85.6% Cu recovery and the commissioned concentrator subsequently averaged 84.7%, providing a rare published example of strong bench-to-pilot-to-plant continuity (Lotter et al., 2024).

This review therefore asks a different question from the traditional formulation: "What scale-up factor should be used?" The central question is which mechanisms must be preserved, reproduced, or explicitly modeled for laboratory performance to remain predictive at industrial scale. The review compares unit operations within one engineering framework, identifies recurrent failure mechanisms, evaluates evidence maturity from bench testing to commercial operation, and culminates in the MINESCALE decision-gate framework.

The principal contribution is not a new universal scaling equation. It is a cross-operation concept of transferability that separates equipment sizing from evidence maturity and then extends validation from the local unit to the smallest integrated system that contains the feedbacks controlling the engineering decision. This distinction runs throughout the review, connecting ore variability, hydrodynamics, liberation, rheology, residence-time distributions, recycles, control dynamics, model validation, and commissioning evidence.

2. REVIEW METHODOLOGY AND EVIDENCE FRAMEWORK

2.1 Review design, scope, and search architecture

This work is a structured critical narrative review rather than a PRISMA-style systematic review or a statistical meta-analysis. That distinction is deliberate: scale-up evidence is highly heterogeneous in equipment architecture, ore type, operating scale, model form, and industrial reporting, and many of the most decision-relevant contributions are single industrial surveys, commissioning studies, pilot campaigns, or validated engineering models that cannot be pooled into a common effect size.

The primary evidence window was January 2020 to 5 September 2026. The search architecture comprised 150 operation-specific Boolean queries and 20 cross-cutting queries addressing scale-up $\times$ ore variability, representativeness, mineralogy, liberation, rheology, hydrodynamics, RTD, energy, control, recycle, flowsheet integration, bench-to-pilot and pilot-to-industrial transfer, and external model validation. Search strings were designed to be Google Scholar-compatible and were iteratively broadened when the exact phrase "scale-up" excluded relevant industrial work that instead used terms such as pilot, full-scale, plant survey, commissioning, industrial validation, transferability, or performance prediction. We verified candidate records against publisher and DOI metadata and used backward and forward citation chaining for high-value cross-scale studies.

The bibliography contains 144 contemporary sources in the primary window—15 from 2020, 16 from 2021, 21 from 2022, 16 from 2023, 31 from 2024, 24 from 2025, and 21 from 2026—plus six foundational works outside the window. The older sources were included only where they anchor canonical concepts that remain directly relevant to present scale-up practice, including Bond energy scaling, hydrocyclone modeling, sedimentation theory, industrial flotation gas-dispersion relationships, comminution-circuit design, and flowsheet modeling (Bond, 1952; Gorain et al., 1997; King, 2001; Kynch, 1952; Napier-Munn, 1996; Plitt, 1976).

2.2 Eligibility criteria and study selection

Studies were retained when they contributed directly to at least one of four review questions: (i) what state or mechanism changes with scale; (ii) which variable controls the target performance response; (iii) how laboratory, pilot, model, or industrial transferability was tested; and (iv) what uncertainty remains after scale-up. Priority was given to studies that crossed at least one evidence boundary—bench to continuous laboratory, bench to pilot, pilot to demonstration, pilot to industrial, or calibrated model to independent plant data—because such comparisons reveal failure modes that single-scale studies cannot expose.



We excluded studies from the core synthesis that reported only routine process performance without a scale-transfer implication, used a model without sufficient information on calibration or validation for the claim, or concerned a material or unit operation only tangentially related to mineral-processing scale-up. Review papers and institutional sources framed concepts or identified evidence gaps but were not treated as equivalent to direct cross-scale validation.

2.3 Evidence coding and critical appraisal

Each retained study was interpreted using six appraisal domains: physical evidence level; feed representativeness; dominant mechanism or state variable; continuity and recycle representation; model and measurement validation; and industrial-scale external validity. The appraisal was intentionally qualitative rather than collapsed into a single numerical quality score, because a CFD validation, a pilot campaign, a commissioning survey, and a geometallurgical variability study answer different scale-up questions. Evidence was weighted most strongly when the claimed transfer relationship was tested against a state that did not define the calibration itself.

The review also distinguishes equipment-scale validation from flowsheet-scale validation. A commercially mature unit can still be a weak basis for a new project if upstream liberation, recycle-water chemistry, solids inventory, ore-domain variability, or downstream dewatering have not been reproduced. Conversely, a well-designed continuous laboratory campaign can provide stronger evidence than a nominally larger pilot if the pilot feed is unrepresentative or if critical recycle and control states are open.

2.4 Evidence hierarchy

Table 1 formalizes the evidence levels used throughout the review. Physical scale and evidence maturity are intentionally separated: size alone does not determine decision value.

Table 1. *Evidence levels used to evaluate mineral-processing scale-up*

Evidence level	Typical configuration	Primary scale-up question	Principal limitation / value
Bench/laboratory	Batch or short-duration testing with tightly controlled feed	Identify intrinsic response, mechanisms, and parameter sensitivity	High mechanism resolution; low representation of continuity and recycle
Continuous laboratory	Continuous or locked-cycle operation with controlled inventory	Expose RTD, recycle, and steady-state effects	Bridges batch response and pilot dynamics
Pilot	Representative continuous equipment and feed rate	Test hydrodynamics, transport, capacity, and operability	Strongest pre-design evidence when feed and states are representative
Demonstration	Pre-commercial equipment or integrated module	Confirm reliability, control, and prolonged operation	Tests maintainability, variability, and disturbances
Industrial module	Commercial-scale unit in operating plant	Validate capacity, selectivity, and model extrapolation	High external validity for the equipment
Integrated commercial plant	Full flowsheet with recycles and control loops	Validate circuit-scale transferability	Strongest evidence for system performance

Note. Definitions are an engineering synthesis conceptually adapted from staged testwork, commissioning, digitalization, and industrial-validation evidence (de Jong, 2024; Felipe et al., 2026; Han et al., 2026; Lotter et al., 2024; Nad et al., 2022; Ohenoja et al., 2023; Rodriguez et al., 2026; Välikangas et al., 2025).



A pilot is not automatically a stronger predictor than a continuous laboratory campaign if the pilot feed is unrepresentative, recycle is open, or the operating state differs from the industrial target. Conversely, a mechanistic or data-driven model gains scale-up decision value only when validation is independent of the calibration data and the model is exercised within a demonstrated domain.

2.5 Review limitations and reproducibility boundary

Because the review is a structured critical narrative synthesis rather than an exhaustive database review, the bibliography should not be interpreted as a complete census of every mineral-processing scale-up publication. Search-engine ranking, incomplete publication of unsuccessful industrial campaigns, proprietary plant data, vendor-led technology reporting, and variable terminology across unit operations create unavoidable retrieval and publication biases. Section 12.5 addresses these limitations explicitly. Appendix A reports the 20 complete cross-cutting search strings used to interrogate the synthesis so that the review logic can be reproduced and extended; the 150 operation-specific queries are not reproduced in full in the main manuscript because of length.

3. FUNDAMENTALS OF SCALE-UP IN MINERAL PROCESSING

3.1 Similarity is multidimensional

Classical scale-up separates geometric, kinematic, and dynamic similarity, but mineral-processing systems add particle-scale, interfacial, and population-balance constraints that often make simultaneous preservation of all similarity criteria impossible. A flotation cell may preserve superficial gas velocity while changing turbulence spectra and froth transport; a mill may preserve specific energy while changing impact distributions and slurry transport; and a hydrocyclone may preserve nominal geometry while feed solids, viscosity, or pressure shift the separation curve (Amini & Xie, 2020; Cleary & Sinnott, 2021; Cleary et al., 2023; Guner et al., 2023; Plitt, 1976; Saeed et al., 2022; Tyeb et al., 2024). Foundational mineral-processing models already recognized that useful scaling requires a process response to be tied to the state variables that generate it rather than to equipment dimensions alone (King, 2001; Napier-Munn, 1996).

The correct engineering response is therefore not to seek one universal similarity law but to identify the small set of dimensionless or state variables that control the target response. Table 2 summarizes the principal criteria used in the recent literature and the type of failure expected when each criterion is violated.

Table 2. *Fundamental similarity criteria relevant to mineral-processing scale-up*

Similarity dimension	Representative criterion	Primary process role	Typical scale-up failure
Geometric similarity	Length ratios and internal proportions	Flow path, active volume, trajectory length	Blind enlargement can change active volume and particle transport
Inertial–viscous balance	Reynolds-type relationships	Mixing, turbulence, pressure loss	Hydrodynamic regime changes
Gravity–inertia balance	Froude-type relationships	Free-surface flow, particle settling, froth drainage	Settling and surface transport become non-similar
Particle–fluid interaction	Slip, Stokes-type response, density contrast	Classification and separation trajectories	Cut size, bypass, and misplaced particles change
Energy similarity	Specific energy, stress energy, power density	Breakage and dispersion environment	Same product size can mask different liberation



Residence-time similarity	Mean and distribution, bypass, dead volume	Kinetics and inventory exposure	Nominal time does not equal effective contact time
Rheological similarity	Yield stress, viscosity, solids concentration	Transport, mixing, settling, and filtration	Scale changes pressure drop, suspension, and cake behavior
Control/dynamic similarity	Disturbance spectrum, actuator authority, recycle inventory	Transient response and stability	Steady laboratory performance fails under plant disturbances

Note. Original synthesis, conceptually adapted from hydrodynamic, grinding, RTD, and modeling evidence (Amini & Xie, 2020; Cleary & Sinnott, 2021; Cleary et al., 2023; Contreras, 2025; Denzel et al., 2026; Guner et al., 2023; Gupta, 2022; Prziwara et al., 2021; Ramos et al., 2022; Saeed et al., 2022; Thivierge et al., 2022; Vinnett et al., 2024).

The relevant criterion depends on the mechanism being scaled, and the same unit may require more than one criterion. These criteria can conflict: maintaining Reynolds-type similarity can violate power-density or particle-settling similarity, while maintaining specific energy can change collision-frequency and stress distributions. This is why modern scale-up increasingly combines empirical tests with calibrated mechanistic, CFD, DEM, PBM, or hybrid models rather than geometric extrapolation alone.

3.2 Capacity is not performance

A recurring error is to equate successful capacity scale-up with successful metallurgical scale-up. Throughput may scale acceptably while changes occur in product PSD, liberation distribution, froth recovery, misplaced fraction, underflow rheology, or cake moisture. Bond's energy approach remains foundational for comminution sizing, but its practical value does not imply that equal specific energy produces equal particle-scale breakage or liberation environments across equipment architectures (Bond, 1952). Population-balance, DEM-CFD, and industrial sensor studies reinforce the need to validate performance variables independently of gross throughput because different internal states can produce the same nominal capacity (Denzel et al., 2026; Gupta, 2022; Ramos et al., 2022; Vinnett et al., 2024).

Industrial performance cannot be treated as the direct consequence of equipment size alone. Rather, it emerges from the combined effects of feed characteristics, preservation of the dominant mechanisms, similarity between scales, residence-time behavior, operating capacity, control dynamics, and circuit recycles. Accordingly, industrial performance may be represented conceptually as:

$$P_{ind} = f(S_{feed}, M, \Pi, RTD, C, D_{ctrl}, R) \quad (1)$$

where P_{ind} is the resulting industrial performance; S_{feed} represents the feed state, including mineralogy, grade, texture, particle-size distribution, liberation, and other relevant variability descriptors; M denotes the dominant performance-controlling mechanisms; Π represents the set of similarity criteria or relevant dimensionless groups that must be preserved or appropriately reproduced across scales; RTD is the residence-time distribution; C represents operating capacity and associated throughput or inventory effects; D_{ctrl} denotes control dynamics, including measurement, response time, control strategy, and process stability; and R represents recycle effects, including circulating loads, water and solids recirculation, reagent carryover, and impurity accumulation.

Equation (1) emphasizes that industrial performance is a multivariable and flowsheet-dependent outcome rather than a simple function of geometric enlargement. Changes in any one of these terms may alter the relative importance of the others. For example, increasing capacity may change hydrodynamics and RTD, which may then affect particle suspension, separation kinetics, control response, and recycle loads. Consequently, successful scale-up requires not only preserving individual equipment-level mechanisms but also verifying that their interactions remain representative under continuous, integrated, industrial operating conditions.

Figure 1 positions scale-up as an evidence pathway rather than a sequence of larger equipment.

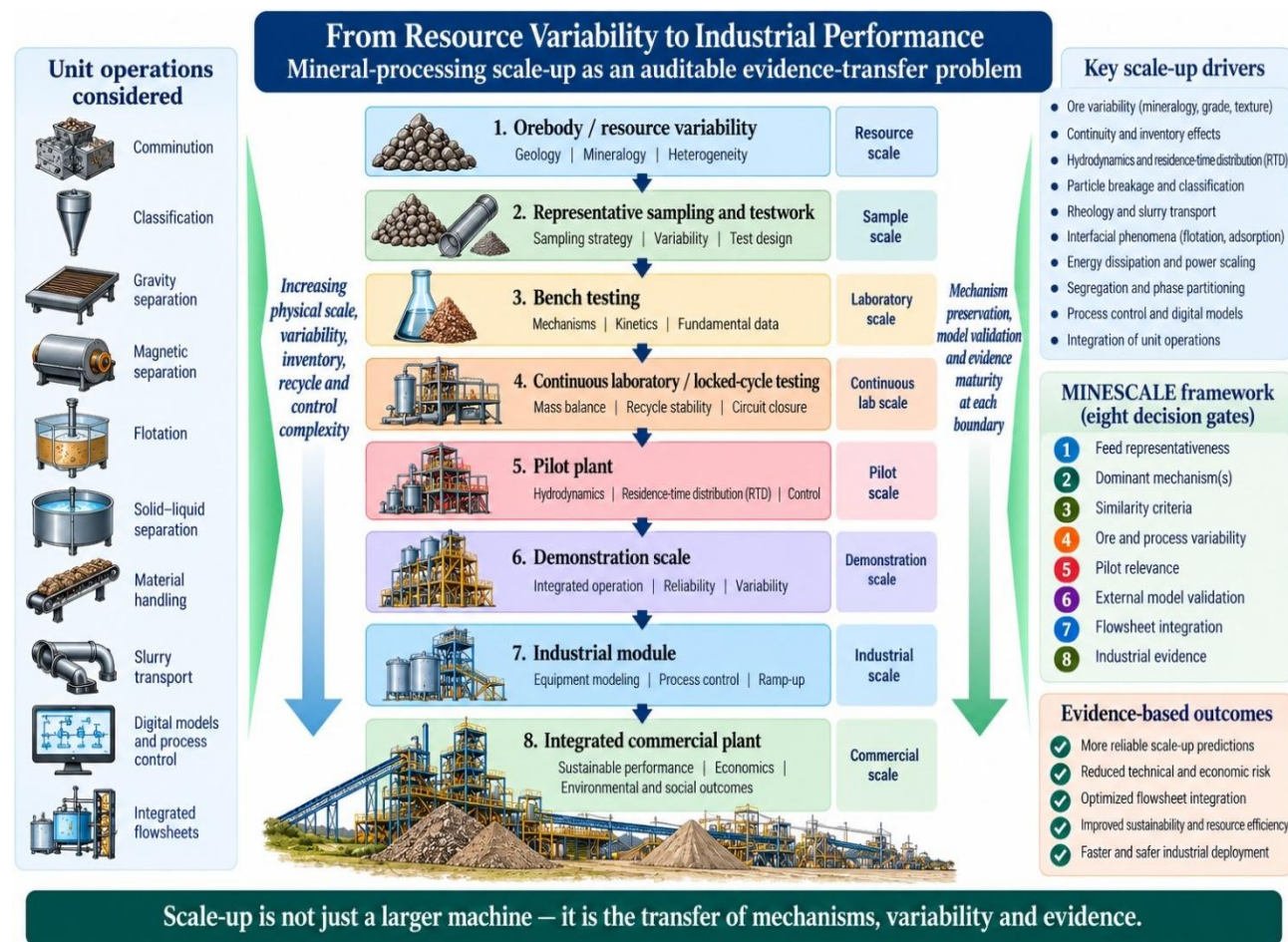


Figure 1. The mineral-processing scale-up hierarchy

Note. Original synthesis by the author; conceptually adapted from evidence on representative sampling, continuous testing, pilot validation, commissioning, and industrial validation (Dominy & Glass, 2025; Hassanzadeh et al., 2024; Lotter et al., 2024; Nad et al., 2022; Rodriguez et al., 2026; Vasconcelos et al., 2026).

Additional scale introduces not only size but also continuity, inventory, feed variability, recycle closure, and control interactions. Each boundary therefore requires a new validation question; successful performance at the preceding scale does not transfer automatically.

Table 3 translates this principle into an operation-by-operation matrix and provides the conceptual backbone for the remainder of the review.

Table 3. What is commonly scaled versus what must be preserved

Operation	Common scaling variable	Mechanism/state to preserve	Principal industrial risk
Crushing	Throughput/crusher size	Breakage distribution and ore competency	Product PSD and power shift with feed and chamber state
Grinding	Installed power/mill volume	Specific energy plus breakage environment and RTD	Same P80 can conceal different liberation



Hydrocyclones	Diameter/number of units	Partition curve, pressure, water split, and solids loading	Bypass, roping, and cluster imbalance
Screening	Area	Bed depth, loading, and stratification	Blinding and misplacement
Gravity / DMS	Area or feed rate	Particle trajectory and density segregation	Trajectory distortion and medium segregation
Magnetic/electrostatic	Throughput	Field–particle interaction and liberation	Reduced selectivity at higher loading
Flotation	Cell volume/residence time	Collection, gas dispersion, mixing, and froth transport	Hydrodynamic and froth-recovery mismatch
Thickening	Area/solids flux	Rheology, hindered settling, and compression	Underflow concentration and torque mismatch
Filtration	Filter area	Cake formation, resistance, and compressibility	Cycle time and final moisture mismatch
Slurry transport	Pipe/pump size	Flow regime, solids suspension, and wear	Settling, pressure loss, and erosion

Note. Original synthesis based on the cross-operation evidence reviewed in Sections 5–10.

The matrix makes explicit that the variable commonly used for sizing is often not the variable that controls transferability. This distinction becomes more important as the process moves from single-unit tests toward circuits with interacting inventories and recycles.

4. ORE VARIABILITY AS THE FIRST SCALE-UP BOUNDARY

4.1 Representativeness precedes similarity

A technically perfect pilot campaign can still be a poor industrial predictor if the test feed does not represent the ore domains that control future plant performance. Geometallurgical studies show that head grade alone is an inadequate state descriptor: mineralogy, texture, grain size, liberation, competency, and rheological behavior can create distinct response domains within a single deposit. Sampling and testwork must therefore preserve the distribution of process-relevant attributes, not merely the average assay (Both & Dimitrakopoulos, 2022; Dominy & Glass, 2025; Rodovalho et al., 2025; Tiu et al., 2023; Tungpalan et al., 2021).

The first scale-up gate is consequently a feed-definition gate. Ore variability affects not only metallurgical response but also the equipment's internal physics: breakage functions, slurry rheology, classification efficiency, froth behavior, magnetic response, and solids handling can all change before any equipment parameter is altered. Statistical rheology work and industrial magnetic-separation evidence illustrate how particle composition and size alter transport or separation states, while liberation estimators show why the process state must be described at particle scale (Bazin et al., 2024; Contreras et al., 2020; Pérez-García et al., 2020; Pérez-García et al., 2021; Semsari Parapari et al., 2020).

4.2 Variability must be propagated through the flowsheet

Ore variability is rarely local to the first affected unit. Changes in competence alter mill loading and circulating load; changes in liberation modify downstream separation; and changes in rheology propagate into flotation, transport, thickening, and filtration. Dynamic optimization under geological uncertainty and blended-ore flotation models show that a scale-up design must be tested across an ore-domain envelope rather than only at a nominal design point (Kabemba et al., 2025; Käyhkö et al., 2022; Runge et al., 2024).

Figure 2 summarizes the mechanisms that can destroy transferability even when equipment geometry is nominally similar.

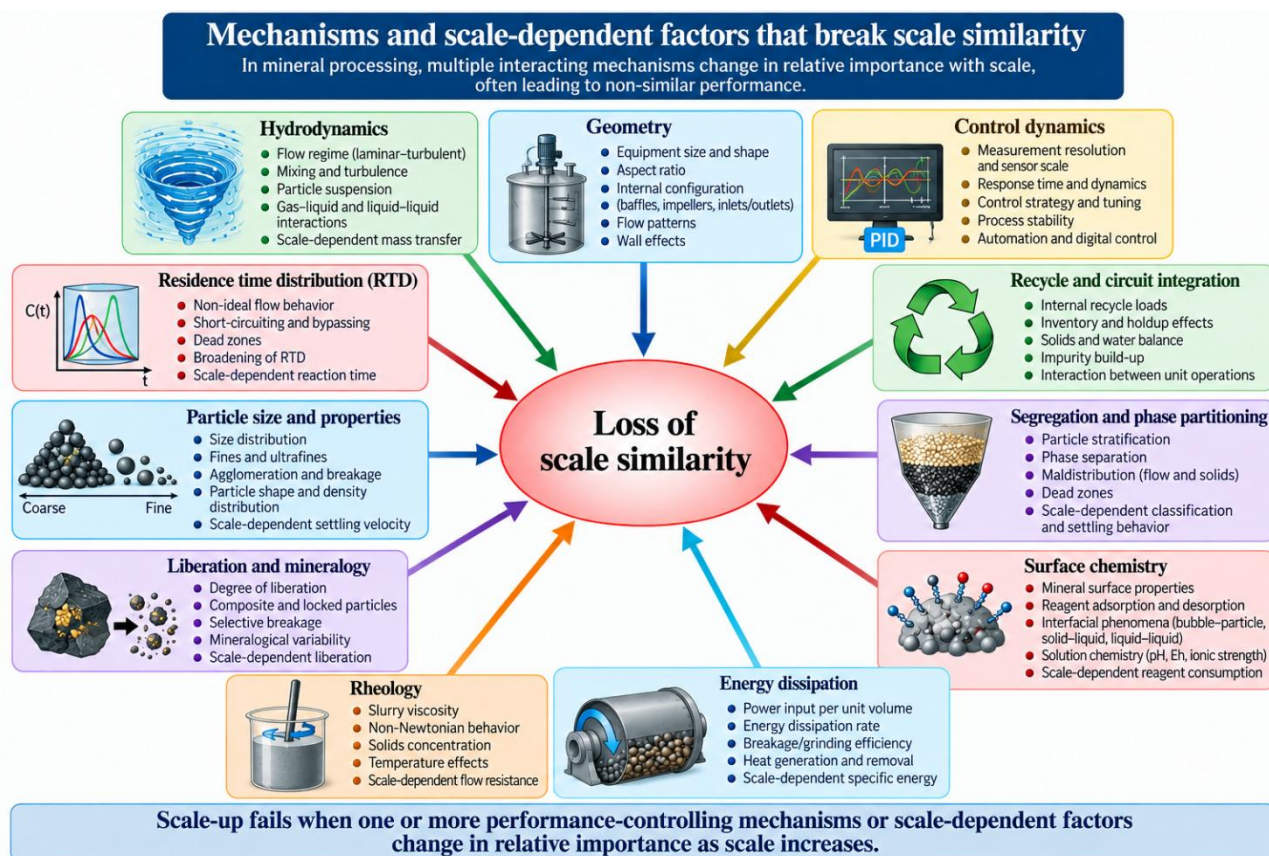


Figure 2. Mechanisms that break scale similarity

Note. Original synthesis by the author; conceptually adapted from evidence on ore variability, hydrodynamics, RTD, rheology, liberation, recycle, and control (Cleary et al., 2023; Contreras et al., 2020; Contreras, 2025; Moraga et al., 2022; Tiu et al., 2023; Wepener et al., 2021; Yianatos & Vallejos, 2024).

The mechanisms in Figure 2 interact. A shift in particle size can simultaneously alter rheology, hydrodynamics, residence time, and segregation. Empirical scale factors can therefore remain valid inside a narrow calibration envelope but fail when industrial feed or operating state moves outside that envelope.

5. CRUSHING, GRINDING, AND COMMINUTION SCALE-UP

5.1 Crushing and primary size reduction

Crusher scale-up increasingly combines breakage models with DEM and industrial surveys. Cone-crusher studies link chamber conditions to throughput, product size, and specific energy, while recent jaw-crusher simulations validate particle-scale models against industrial surveys before using them to explore geometry, feed size, and capacity. These studies support a mechanism-based route in which breakage response is calibrated first, and geometry is then evaluated through a model that preserves relevant particle-machine interactions (Jiang et al., 2023; Lan et al., 2026; Rodriguez et al., 2026; Yamashita et al., 2021).

Pilot-scale electric-pulse fragmentation provides a contrasting case: the governing loading mechanism differs from conventional compression and therefore cannot be transferred through crusher dimensions alone. The broader implication is that "crushing scale-up" is not a single problem; it depends on whether the technology preserves contact mechanics, stress distribution, residence time in the chamber, and the feed's breakage response (Bru et al., 2020; Semsari Parapari et al., 2020).



5.2 AG/SAG and ball milling

SAG scale-up exposes the limitations of geometric similarity particularly clearly. Particle-scale modeling of pilot and industrial SAG mills shows that charge structure, slurry transport, discharge, and collision-energy distributions do not remain identical simply because dimensions are scaled. Pilot campaigns on itabirite and industrial data-driven work further show that ore type, circulating load, and control state must be part of the transfer function (Cleary et al., 2023; Ghasemi et al., 2025; Liao et al., 2026; Rodrigues et al., 2021).

For ball milling, population-balance approaches remain useful when breakage and selection functions are calibrated within a physically relevant domain. However, the mill-diameter scale-up exponent is not universal and can vary with the size distributions of grinding media and particles. Industrial dry-grinding validation also shows the value of including classifiers and comparing model predictions across multiple parallel plant lines, rather than validating the mill in isolation (de Jong, 2024; Gupta, 2022; Göktaş et al., 2023). Classical Bond and JKMRC approaches remain indispensable design anchors, but recent evidence clarifies when their energy or circuit relationships must be supplemented with mechanism-specific state variables (Bond, 1952; Napier-Munn, 1996).

5.3 HPGR and stirred mills

HPGR provides one of the richest recent evidence bases for mechanistic, multiscale development. Industrial surveys, pilot-calibrated DEM-PRM models, piston-press methods, sizing equations, and full industrial circuit evaluations converge on the need to preserve stress, throughput, moisture, feed size, and operating-pressure effects. The studies collectively show that scale-up should be treated as a calibrated operating envelope rather than as a fixed diameter or power law (Campos et al., 2021; Cleary & Sinnott, 2021; Guo et al., 2024; Li et al., 2023; Massinaei & Javanshiri, 2026; Morrell, 2022; Pamparana et al., 2022; Rodriguez et al., 2022; Saramak & Leśniak, 2024; Thivierge et al., 2022).

Stirred mills show a similar movement from energy-only criteria toward stress and hydrodynamic descriptions. Pilot-to-full-scale comparisons, signature-plot methods, industrial PBM, DEM-CFD torque models, and stress-based performance approaches show that specific energy remains necessary but is insufficient when stress intensity, media distribution, RTD, wear, and slurry transport change with scale (Altun et al., 2023; Altun et al., 2024; Bilgili et al., 2024; Can & Altun, 2023; Denzel et al., 2026; Li et al., 2024; Prziwara et al., 2021; Taylor et al., 2020). Table 4 summarizes the critical scale-up approaches and validation requirements identified for comminution.

Table 4. *Critical scale-up approaches for comminution*

Operation	Dominant approach	State variables that require validation	Key failure mode
Crushers	DEM + breakage model; industrial survey calibration	Throughput, PSD, chamber state	Calibration must span ore competency and feed-size envelope
AG/SAG	Pilot testing; DEM/particle-scale modeling; data-driven optimization	Charge structure, collision energy, slurry transport, circulating load	Geometric similarity does not preserve internal dynamics
Ball mills	PBM; breakage/selection functions; circuit calibration	Specific energy, RTD, classifier interaction	Scale factor is material- and condition-dependent
HPGR	Piston press + pilot; DEM-PRM; industrial surveys	Specific pressing force, moisture, throughput, product fineness	Calibration-domain extrapolation and wear



Stirred mills	Signature plots; stress analyses; PBM; DEM-CFD	Stress energy, media motion, RTD, torque, and wear	The same energy can produce different stress environments
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Note. Synthesized from recent crushing, milling, HPGR, and stirred-mill studies (Altun et al., 2023; Altun et al., 2024; Bilgili et al., 2024; Campos et al., 2021; Can & Altun, 2023; Cleary & Sinnott, 2021; Cleary et al., 2023; de Jong, 2024; Denzel et al., 2026; Guo et al., 2024; Gupta, 2022; Jiang et al., 2023; Lan et al., 2026; Li et al., 2023; Li et al., 2024; Massinaei & Javanshiri, 2026; Morrell, 2022; Pamparana et al., 2022; Prziwara et al., 2021; Rodrigues et al., 2021; Rodriguez et al., 2022; Rodriguez et al., 2026; Saramak & Leśniak, 2024; Taylor et al., 2020; Thivierge et al., 2022; Wilson et al., 2024; Yamashita et al., 2021).

The strongest comminution studies combine calibration at one scale with external validation at another. They also increasingly treat classification, circulating load, and control as part of the comminution system, anticipating the circuit-level discussion in Section 11.

6. CLASSIFICATION AND PARTICLE-SIZING OPERATIONS

6.1 Hydrocyclones: cut size is a state, not a constant

Hydrocyclone scale-up is often simplified to diameter and nominal capacity, yet both classical and recent work show that corrected cut size and partition behavior depend on geometry and operating state. Plitt's model formalized the dependence on cyclone dimensions, pressure, and solids, while recent studies extend this to feed PSD, density distribution, inlet velocity, particle interactions, and high-solids multicomponent feeds (Daza et al., 2020; Padhi et al., 2021; Plitt, 1976; Wang et al., 2024; Xiong et al., 2023; Zhang & Lu, 2023).

Roping is particularly important because it introduces a nonlinear regime transition. Online vibration detection and recent evidence of roping hysteresis indicate that the operating state can depend on operating history, not only instantaneous input variables. This path dependence directly challenges laboratory-to-plant transfer when tests do not reproduce industrial operating history, including excursions, or solids inventory (Mishra et al., 2024; Tyeb et al., 2025).

6.2 Screens and classifiers as circuit elements

An industrial comparison of hydrocyclones and high-frequency screens shows that classification scale-up cannot be evaluated locally. Changes in bypass, water split, and partitioning alter circulating load and hence mill residence time, power demand, liberation, and downstream feed. In a simulation grounded in industrial lead-zinc grinding data, replacing hydrocyclones with high-frequency fine screens increased predicted throughput by 13% while reducing specific grinding energy by 15%, illustrating how a classifier decision propagates into mill performance (Dündar, 2020). Industrial surveys and DEM/CFD screen models reinforce the same circuit-level coupling (Costa et al., 2024; Jaiswal et al., 2025; Soni et al., 2023).

Inclined-channel and reflux-classification research extends the argument to hydrodynamic classifiers: capacity depends on the interaction among geometry, solids loading, and particle settling trajectories. Scale-out by adding parallel units can be safer than enlarging a single separator only when feed distribution is sufficiently uniform; in industrial clusters, manifolds, pressure variability, and feed segregation may dominate scale-up challenges even when each unit is well characterized. Table 5 summarizes the principal scale-up variables and risks for classification and physical separation.

Table 5. *Scale-up variables for classification and physical separation*

Operation	Performance descriptor	Variables that must be preserved or modeled	Principal risk
Hydrocyclone	Cut size, bypass, water split, pressure, roping	PSD, solids, density, apex/vortex dimensions, feed history	Partition curve changes with state; cluster imbalance



Vibrating screen	Area, bed depth, stratification, misplacement	Feed rate, PSD, vibration, and panel properties	Blinding or insufficient stratification at scale
Hydrodynamic classifier	Solids flux and inclined-channel geometry	Settling velocity, hindered settling, flow distribution	Capacity increase changes trajectory field
Dense-medium cyclone	Partition curve and medium stability	Medium segregation, inlet head, spigot, density control	Misplacement and medium loss
Gravity separator	Particle trajectory and stratification	Pulsation, slurry flow, density/size distribution	Scale changes segregation path
Magnetic/electrostatic	Field–particle interaction and loading	Liberation, mineral composition, field intensity, residence	Throughput increase reduces selectivity

Note. Synthesized from hydrocyclone, screening, dense-medium, gravity, magnetic, and electrostatic studies (Ambrós, 2020; Baawuah et al., 2020; Bazin et al., 2024; Coelho et al., 2025; Costa et al., 2024; Daza et al., 2020; Dündar, 2020; Hosseini Alaei, Samieinejad, et al., 2025; Hosseini Alaei, Sargheyne, et al., 2025; Huang et al., 2026; Jain, 2021; Jaiswal et al., 2025; Kumar et al., 2021; Lowry et al., 2024; Mishra et al., 2024; Mokgomola et al., 2025; Padhi et al., 2021; Pereira, 2026; Raposo et al., 2024; Soni et al., 2023; Starrett & Galvin, 2025; Tyeb et al., 2024; Tyeb et al., 2025; Wang et al., 2024; Xiong et al., 2023; Yi et al., 2024; Zhang & Lu, 2023; B. Zhang et al., 2025).

7. GRAVITY, MAGNETIC, ELECTROSTATIC, AND OTHER PHYSICAL SEPARATION

7.1 Gravity and dense-medium separation

Gravity separation is trajectory-controlled. Jigging and spiral studies show that stratification, pulsation, secondary circulation, and slurry distribution evolve dynamically, so the relevant transfer variable is not simply deck area or feed rate. Pilot spiral studies and dry-jig work demonstrate that increased capacity must preserve the trajectory field and residence conditions that create density and size stratification (Ambrós, 2020; Hosseini Alaei, Samieinejad, et al., 2025; Hosseini Alaei, Sargheyne, et al., 2025; Jain, 2021; Raposo et al., 2024).

Dense-medium separation adds a coupled fluid-particle field. Pilot DMS work, industrial dynamic modeling, and dense-medium cyclone studies show that medium segregation, spigot geometry, inlet head, and medium losses change partition performance. These effects are particularly important when laboratory heavy-liquid results are used to justify pilot or plant pre-concentration without representing the hydrodynamic behavior of the actual medium circuit (Kumar et al., 2021; Lowry et al., 2024; Mokgomola et al., 2025).

7.2 Magnetic, electrostatic, and eddy-current separation

Magnetic scale-up is constrained by the interaction among mineral composition, liberation, field distribution, and solids loading. Industrial WLIMS/WHIMS surveys, full-scale centrifugal dry magnetic separation, and full-scale cHGMS developments show that commercial capacity can be achieved, but only when magnetic-circuit design and feed preparation preserve the relevant field–particle interactions (Baawuah et al., 2020; Bazin et al., 2024; Huang et al., 2026; Yi et al., 2024; B. Zhang et al., 2025).

Electrostatic and eddy-current systems similarly depend on particle trajectory, charging or induced-current response, size distribution, and liberation. Pilot triboelectrostatic separation using industrial phosphate samples provides direct intermediate-scale evidence, while the critical review of eddy-current separation highlights design limits and industrial scale-up constraints in non-ferrous separation. The broader lesson is that "physical" separation does not imply simple geometric scalability; selectivity remains a particle-scale interaction



expressed through equipment-scale trajectories (Coelho et al., 2025; Pereira, 2026).

8. FLOTATION SCALE-UP

8.1 From kinetic factors to mechanism-based transfer

Flotation has the most extensive direct scale-up literature because its performance depends simultaneously on particle properties, bubble–particle encounter, attachment and detachment, gas dispersion, mixing, entrainment, and froth transport. Studies comparing laboratory, mini-pilot, and industrial cells show that a single batch-to-plant factor is not universal and that particle size and liberation materially alter the transfer relationship (Awatey et al., 2026; Hassanzadeh et al., 2024; Iveson et al., 2022; Vasconcelos et al., 2026; Yianatos et al., 2022). In industrial rougher circuits, Yianatos et al. (2022) reported average batch-to-plant factors of approximately 1.8–2.2 for copper sulfide minerals, but values increased from roughly 1.5 at fine sizes toward 3–4 for coarse and less-liberated particles. This direct evidence rules out treating the factor as a material-independent constant.

Kinetic extrapolation is particularly vulnerable when effective collection volume, RTD, or froth recovery changes with scale. Industrial effective-volume estimates, REFLUX-cell RTD measurements, and improved froth-recovery models demonstrate that nominal residence time can overstate the time actually available for collection and can omit transport losses in the froth phase (Guner et al., 2023; Neethling et al., 2024; Vinnett et al., 2024; Yianatos & Vallejos, 2024).

The implication is that intrinsic floatability should be separated from equipment-specific encounter and transport. Recent phenomenological modeling provides one route for connecting batch and continuous systems by distinguishing intrinsic floatability from hydrodynamic and saturation effects, while simulator and liberation-based approaches provide complementary routes for predicting grade–recovery response (Huang et al., 2022; Polat et al., 2026).

8.2 Hydrodynamics, gas dispersion, and measurement

Scale-up requires direct measurement of the hydrodynamic state. Foundational industrial work linked flotation kinetics to bubble surface-area flux rather than to superficial gas velocity, gas holdup, or bubble size considered in isolation, providing an early demonstration that mechanism-based hydrodynamic descriptors can transfer across equipment configurations (Gorain et al., 1997). Recent turbulence-based scale-up methods, gas-holdup sensors validated in industrial cells, large-cell submersible instrumentation, and CFD studies similarly show that plant-scale gas dispersion and turbulence cannot safely be inferred from geometry alone (Afzali Gorouh et al., 2026; Amini & Xie, 2020; Anzoom et al., 2020; Dohm et al., 2022; Ramos et al., 2022; Saeed et al., 2022; M. Zhang et al., 2025).

Coarse-particle flotation adds transport constraints because bubble loading, detachment, and carrying capacity can become limiting. Fine-particle systems face the opposite problem: ultrafines alter pulp viscosity, entrainment, and froth stability. These opposing regimes explain why intensified flotation technologies often require architecture-specific scale-up procedures rather than inherited residence-time rules (Hassanzadeh et al., 2022; Jameson & Emer, 2024; McFadzean et al., 2023; Nasset et al., 2025).

8.3 Reagents, water chemistry, and flowsheet state

Chemical state also changes with scale. Reagent-system upscaling, industrial water recycling, and residual dewatering aids show that plant water is a chemically active process stream. Locked-cycle or pilot testing that does not close the water circuit can therefore overestimate transferability even when hydrodynamic similarity is acceptable (Ben Said et al., 2025; Di Feo et al., 2021; Lin et al., 2020; Manono et al., 2024; Michaux et al., 2020). Table 6 consolidates the mechanism-based interpretation of flotation scale-up.



Table 6. *Mechanism-based interpretation of flotation scale-up*

Scale-up domain	What is transferred	Critical variables	Engineering implication
Kinetics / floatability	Batch vs continuous response; intrinsic floatability	Rate constant, size/liberation, RTD	Avoid a single global batch-to-plant factor
Hydrodynamics	Turbulence, gas holdup, superficial gas velocity	Mixing intensity, bubble size, active volume	Measure industrial state; do not infer from geometry
Froth transport	Froth recovery, bubble loading, carrying capacity	Froth depth, drainage, particle size	Collection recovery does not equal overall recovery
Intensified cells	Reactor–separator, fluidized, and pneumatic cells	Architecture-specific contact and transport	Conventional residence-time rules may not transfer
Circuit validation	Cycle tests, pilot circuits, industrial validation	Recycle, classification, water chemistry	Validation must close material and water loops

Note. Synthesized from laboratory, pilot, industrial, and modeling studies (Afzali Gorouh et al., 2026; Amini & Xie, 2020; Anzoom et al., 2020; Awatey et al., 2026; Ben Said et al., 2025; Dohm et al., 2022; Guner et al., 2023; Han et al., 2026; Hassanzadeh et al., 2022; Hassanzadeh et al., 2024; Hassanzadeh & Hoang, 2026; Huang et al., 2022; Iveson et al., 2022; Jameson & Emer, 2024; Ko et al., 2026; Käyhkö et al., 2022; McFadzean et al., 2023; Neethling et al., 2024; Nesset et al., 2025; Ohenoja et al., 2023; Ostadrahimi et al., 2021; Polat et al., 2026; Ramos et al., 2022; Saeed et al., 2022; Sepúlveda et al., 2024; Sun et al., 2025; Vasconcelos et al., 2026; Vinnett et al., 2024; Yianatos et al., 2022; Yianatos & Vallejos, 2024; M. Zhang et al., 2025).

The flotation literature therefore warns against treating any scale-up factor as universal. A defensible factor depends on particle population, cell architecture, hydrodynamic regime, RTD, and froth transport and should be validated under continuous or industrial operating conditions whenever an investment decision depends on it.

Studies that industrially validate novel columns, pilot scheelite circuits, cycle-test optimization, and laboratory-to-industrial gold-telluride flotation demonstrate the value of staged evidence. These studies are strongest when they show not only increased recovery but also that the scale-up basis remained predictive after changes in circuit, feed, and control environment (Han et al., 2026; Sepúlveda et al., 2024; Sun et al., 2025; Vasconcelos et al., 2026).

9. SOLID–LIQUID SEPARATION AND DEWATERING

9.1 Thickening: settling becomes compression and rheology

Thickener scale-up cannot stop at free-settling tests because industrial beds evolve from hindered settling into compression, shear, and drainage through a structured solids network. Kynch's sedimentation theory remains a foundational starting point, but recent work on bed drainage channels, permeability, rake shearing, and high-compression behavior shows that underflow concentration and torque are controlled by coupled rheology and consolidation rather than by plan area alone (Chen et al., 2023; Chen et al., 2024; Jiao et al., 2021; Kynch, 1952; Wang et al., 2025; Wu et al., 2024; Wu et al., 2026).

Design methods that combine rheology, sedimentation, and compression parameters are therefore more transferable than area-only scaling. The central engineering challenge is to reproduce the stress and shear history that governs the underflow state, particularly for fine tailings whose yield behavior evolves strongly with concentration (Quiero et al., 2024; Wang et al., 2025; Wu et al., 2024; Wu et al., 2026).



9.2 Filtration and centrifugation

Filtration scale-up is governed by cake formation, permeability, compressibility, desaturation, and the interaction between pressure and cake thickness. Ceramic-capillary, filter-press, and copper-tailings studies demonstrate that laboratory-measured specific resistance is informative only when cake structure and pressure history are representative of the industrial cycle (Araujo et al., 2022; Fränkle et al., 2022; Fränkle et al., 2024).

New dewatering technologies add a scale-up challenge. High-pressure rolls, microwave dewatering, and pilot centrifuges show that energy use, transport, and fine-particle recovery may differ from bench to pilot scale. Chemical pretreatment can improve slime-rich tailings permeability by altering interparticle forces, but reagent carryover and downstream water reuse must also be assessed (Felipe et al., 2026; Hassan et al., 2025; Marzoughi et al., 2026; Muñoz et al., 2026). Table 7 summarizes scale-up bases and risks for thickening and dewatering.

Table 7. *Scale-up basis for thickening and dewatering*

Operation	Dominant mechanism	Parameters requiring representative testing	Primary scale-up risk
Thickening	Settling + compression + shear	Solids flux, yield stress, permeability, bed height	Underflow concentration and rake torque
Pressure filtration	Cake formation under pressure	Specific resistance, compressibility, thickness	Cycle time and residual moisture
Vacuum / ceramic filtration	Capillary pressure and desaturation	PSD, permeability, surface chemistry	Scale-dependent cake structure
Centrifugation	Centrifugal settling and solids transport	g-force, residence, solids loading	Fine recovery and throughput
Novel dewatering	Combined mechanical/thermal route	Energy intensity, continuous solids transport	Pilot efficiency differs from bench response

Note. Synthesized from thickening, filtration, centrifugation, and dewatering studies (Araujo et al., 2022; Chen et al., 2023; Chen et al., 2024; Felipe et al., 2026; Fränkle et al., 2022; Fränkle et al., 2024; Hassan et al., 2025; Jiao et al., 2021; Marzoughi et al., 2026; Muñoz et al., 2026; Quiero et al., 2024; Wang et al., 2025; Wu et al., 2024; Wu et al., 2026).

The common thread across Table 7 is structure formation. Whether the structure is a compressing thickener bed or a filter cake, the laboratory test must reproduce the stress, concentration, and shear path that controls permeability and final solids properties. Scaling surface area without scaling this history is not a robust design basis.

10. MATERIAL HANDLING, SLURRY TRANSPORT, AND AUXILIARY OPERATIONS

Material handling is often omitted from scale-up reviews even though industrial capacity is frequently determined by the most restrictive transfer point rather than by the nominal capacity of major process equipment. DEM- based chute studies show that moisture, cohesion, PSD, and operating variability can

produce blockage, segregation, and highly nonlinear wear, while dry iron-ore flowability work links bench characterization directly to industrial design needs (Basu et al., 2021; Hadi et al., 2024; Ou & Chen, 2022; Silva et al., 2025). More recent chute work demonstrates that liner geometry and particle size can alter wear intensity by changing whether particles slide on the liner or flow over a protective particle layer (Grasser et al., 2024).

Bins and hoppers introduce a second boundary of variability. DEM analysis of polydisperse hopper discharge shows that PSD width changes mass flow and segregation, meaning a nominally adequate bin can alter the size distribution presented to downstream crushers, screens, or mills even when its average discharge rate is acceptable (Kumar et al., 2020). The relevant scale-up questions are not only "Will the bin discharge?" but also "Will it discharge the same particle population and temporal variability assumed by the downstream process model?"

Slurry transport adds a coupled rheology–hydraulics–wear problem. CFD surrogate models for pressure drop, large-scale slurry-pump field comparisons, and rheology-focused transport reviews show that pipe diameter or pump size is not a sufficient scale variable. Solids suspension, bimodal PSD, viscosity, yield stress, velocity distribution, and erosive particle trajectories determine whether a design remains stable at industrial scale (Elkarii et al., 2023; Peng et al., 2020; Pradhan, 2026). Pump duty must also be assessed against the actual slurry envelope because changes in density, wear, and gas entrainment can reduce the available hydraulic margin long before nominal motor power is reached.

Conveyors and auxiliary systems can become availability-limited bottlenecks rather than instantaneous-capacity bottlenecks. A belt-conveyor digital-twin deployment at an LKAB pilot site shows that condition monitoring and predictive maintenance are needed to protect effective plant capacity over time, not just nameplate throughput (Al-Kahwati et al., 2022). This distinction is central to scale-up because plant throughput depends on the sustained availability of the complete handling chain.

Mixing tanks and surge volumes should be treated in the same way. CFD and experiments on stirred pulp systems show that baffles, draft tubes, and other internals alter circulation and poorly mixed zones; hence, auxiliary equipment can change the feed state presented to the next unit (Li et al., 2021). Surge capacity additionally changes the amplitude and frequency of disturbances seen downstream. A scale-up review that ignores storage, dead zones, mixing, and availability can therefore attribute a downstream mismatch to the wrong unit operation.

Industrial throughput is ultimately constrained by the least-capable unit operation or material-transfer step under sustained operating conditions. Therefore, even when individual equipment items exceed the plant target in nominal capacity, achievable continuous throughput cannot exceed the minimum available capacity of the constraining elements in the integrated flowsheet. This bottleneck condition can be represented as:

$$Q_{plant,sust} \leq \min_{i \in C}(C_{i,avail}) \quad (2)$$

where $Q_{plant,sust}$ is the sustained plant throughput; $C_{i,avail}$ denotes the available operating capacity of unit or transfer step i ; and C denotes the set of potentially constraining unit operations, conveyors, pumps, classifiers, tanks, transfer points, or other flowsheet elements.

Equation (2) emphasizes that plant capacity is a flowsheet-level property rather than a simple sum of individual equipment capacities. The effective bottleneck may shift with ore hardness, particle-size distribution, slurry rheology, circulating load, equipment availability, control constraints, or recycle intensity. Consequently, a unit that is non-limiting under design conditions may become capacity-constraining when feed characteristics or circuit interactions change. Scale-up assessment should therefore evaluate not only nominal equipment ratings but also the available capacity of each potentially restrictive unit under realistic integrated operating conditions.

11. FROM UNIT-OPERATION SCALE-UP TO INTEGRATED FLOWSHEET SCALE-UP

11.1 Circuit-scale transferability

The strongest cross-operation evidence is that scale-up errors propagate. Classification changes circulating load and liberation; flotation changes water and reagent inventories; dewatering changes recycle-water chemistry; and ore blending changes the RTD and composition experienced by multiple units. Dynamic process simulation and plant-wide disturbance studies show that these couplings are not second-order details but part of the industrial state that a pilot or model must reproduce (Göktaş et al., 2023; Lin et al., 2020; Michaux et al., 2020; Moraga et al., 2022; Runge et al., 2024; Wepener et al., 2021; Witecki et al., 2022).

Commissioning studies provide the clearest practical test because the flowsheet, recycle loops, and control structure all become active simultaneously. Kamo-Kakula illustrates the value of representative mineralogical testwork followed by continuous mini-pilot mass/value balancing and commissioning feedback: the 2019 mini-pilot campaign predicted 85.6% Cu recovery, compared with an average recovery of 84.7% after commissioning (Lotter et al., 2024). Integrated mine-to-mill and plant-indicator models further show how geological and mining decisions can propagate into concentrator capacity (Both & Dimitrakopoulos, 2022; Mi et al., 2026).

Water recirculation deserves special emphasis because it couples solid-liquid separation back to flotation. Industrial and simulated water-recycle studies demonstrate that the source, residence time, and chemistry of recycled water alter flotation response; residual dewatering aids provide a direct example of a downstream reagent returning upstream through the water circuit (Di Feo et al., 2021; Lin et al., 2020; Manono et al., 2024; Michaux et al., 2020; Witecki et al., 2022).

Figure 3 shows the transition from local equipment scale-up to circuit-scale transferability.

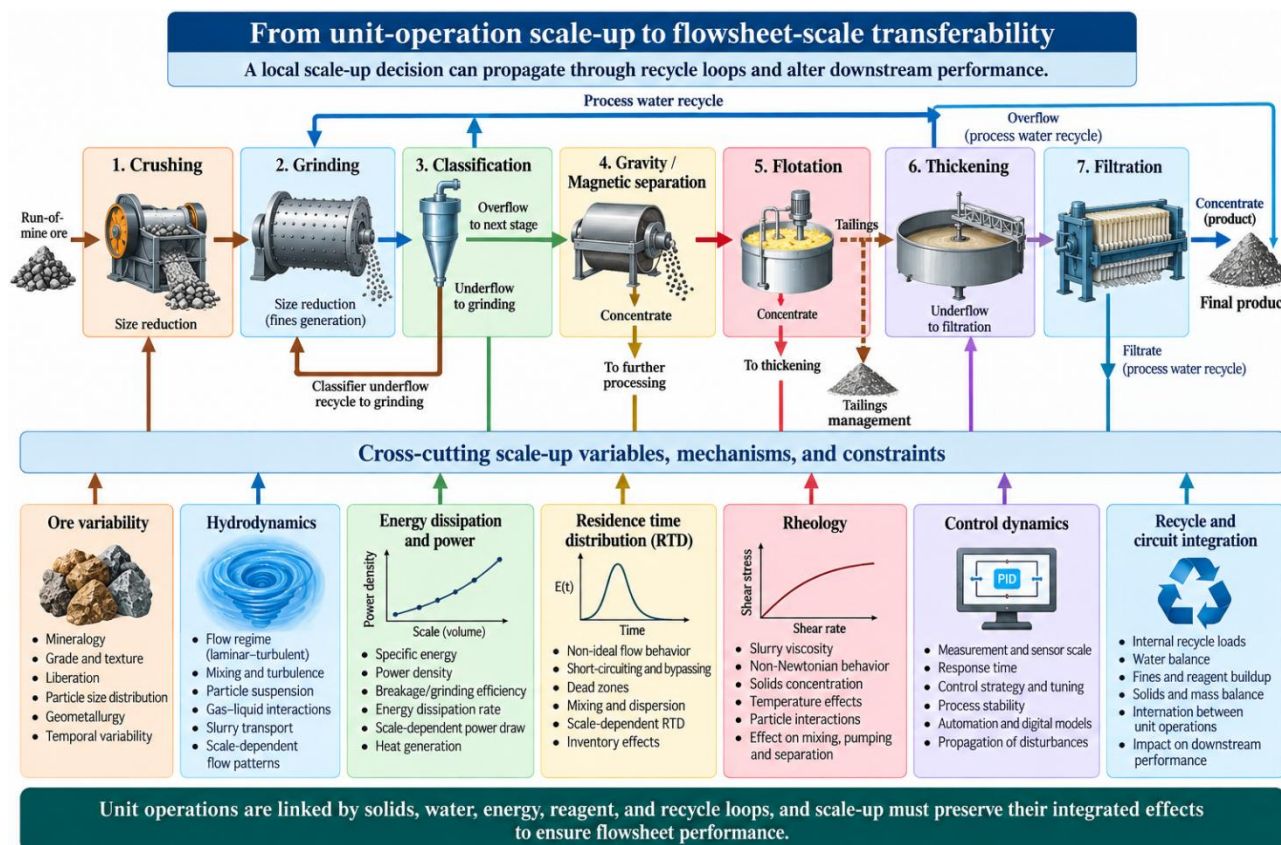


Figure 3. From unit-operation scale-up to flowsheet-scale transferability



Note. Original synthesis by the author; conceptually adapted from integrated grinding–classification, commissioning, water-recycle, and disturbance-propagation evidence (Göktaş et al., 2023; Lotter et al., 2024; Michaux et al., 2020; Moraga et al., 2022; Runge et al., 2024; Wepener et al., 2021).

A unit can therefore be correctly sized yet still underperform in the plant. Recycle loops and cross-cutting state variables modify each unit's boundary conditions, so a scale-up framework must evaluate both equipment response and the stability of the flowsheet state in which that equipment operates. Table 8 summarizes the principal flowsheet couplings that must be represented during scale-up.

Table 8. *Flowsheet couplings that must be represented during scale-up*

Coupling	Transferred state	Downstream consequence	Scale-up implication
Grinding ↔ classification	Circulating load, PSD, water split	RTD, power, liberation	A classifier change alters the mill state
Classification → flotation	Fine bypass and size distribution	Kinetics, entrainment, recovery	Same head grade produces different flotation feed
Dewatering → flotation	Recycle water, residual polymers/ions	Surface chemistry and froth response	Downstream chemistry returns upstream
Ore blending → whole plant	Competency, mineralogy, rheology	Throughput and separation response	Nominal average feed hides dynamic domains
Control ↔ process	Disturbances, inventory, actuator limits	Transient states and stability	Steady pilot tests understate plant excursions
Mine-to-mill	Blast/fragmentation and ore delivery	Crusher/SAG load and downstream liberation	Upstream decisions redefine plant feed

Note. Synthesized from industrial and dynamic flowsheet studies (Both & Dimitrakopoulos, 2022; Di Feo et al., 2021; Ghasemi et al., 2025; Göktaş et al., 2023; Lin et al., 2020; Lotter et al., 2024; Lowry et al., 2024; Manono et al., 2024; Mi et al., 2026; Michaux et al., 2020; Moraga et al., 2022; Runge et al., 2024; Välikangas et al., 2025; Wepener et al., 2021; Witecki et al., 2022).

The practical scale-up boundary is the smallest integrated system that reproduces the feedbacks controlling the decision. For some projects, that boundary may be a closed grinding circuit; for others, it may require locked-cycle flotation with realistic water recycle or a mine-to-mill simulation that includes geometallurgical variability.

11.2 Propagation of scale-up error, bottlenecks, and dynamic inventory

Circuit-scale transferability can be interpreted as a propagation problem. A local state error does not necessarily remain confined to the unit in which it originates, because the affected stream may become the boundary condition for one or more downstream operations. For sufficiently small perturbations, this propagation can be represented conceptually by a first-order sensitivity expression:

$$\Delta P_{\text{plant}} \approx \sum_j (\partial P_{\text{plant}} / \partial x_j) \Delta x_j \quad (3)$$



where ΔP_{plant} is the resulting change in overall plant performance; x_j denotes a transferred process state or boundary condition, such as circulating load, particle-size distribution (PSD), water chemistry, solids inventory, or rheology; Δx_j is the scale-up-induced deviation in that state; and $\partial P_{plant}/\partial x_j$ represents the local sensitivity of plant performance to changes in x_j .

Equation (3) is not proposed as a universal predictive calculation method. Rather, it formalizes the principle that both the magnitude of an upstream scale-up error and the sensitivity of downstream performance to that

error determine its plant-wide consequence. A relatively small deviation in a highly sensitive state variable may therefore propagate more strongly than a larger deviation in a weakly coupled variable. This behavior is especially important in integrated circuits containing recycle streams, inventories, shared water systems, and interacting control loops.

Wepener et al. (2021), for example, showed that disturbances in ore feed, cyclone condition, and sump-water addition can propagate from the grinding circuit into flotation. These interactions show that plant-wide control, disturbance propagation, and flowsheet coupling are intrinsic components of the scale-up problem, not operational considerations that arise only after commissioning.

The same logic applies to capacity. Increasing a major unit above the capacity of the least tolerant chute, pump, classifier, dewatering unit, or conveyor cannot increase sustained plant throughput. Scale-up therefore requires both metallurgical transferability and bottleneck compatibility across the operating envelope, including start-up, feed transitions, maintenance degradation, and recycle transients.

12. A UNIFIED SCALE-UP FRAMEWORK: RISK, VALIDATION, DIGITAL MODELS, AND DECISION GATES

12.1 Models as evidence bridges

Models are most valuable when they bridge an evidence gap rather than merely fit a dataset. PBM, DEM, CFD, mechanistic, hybrid, and machine-learning models represent different parts of the scale-up problem. External validation is the key discriminator: industrial dry-grinding PBM, jaw-crusher DEM, stirred-mill DEM-CFD, and plant-scale HPGR studies provide stronger scale-up evidence than calibration-only models because the models are tested against data or operating states not used in calibration (de Jong, 2024; Denzel et al., 2026; Massinaei & Javanshiri, 2026; Rodriguez et al., 2022; Rodriguez et al., 2026).

Digital twins add continuous updating and disturbance detection. Pilot flotation digital twins, expert-controlled SAG-mill twins, and real-time optimization studies demonstrate the transition from static prediction to adaptive state estimation. Physics-informed surrogate models and mine-to-mill meta-modeling further show how data-driven methods can be constrained by process structure rather than used as unconstrained regressors (Ghasemi et al., 2025; Mancilla et al., 2025; Nobahar et al., 2026; Ohenoja et al., 2023; Quintanilla et al., 2025; Seppi et al., 2025; Zeb et al., 2024).

Digitalization does not remove uncertainty; it makes uncertainty observable. Model-uncertainty propagation and geometallurgical reconciliation studies show why scale-up decisions should report the calibration domain, validation error, and the range of feed states represented in calibration and validation. Online liberation estimators and process-control integration provide an additional route to check whether the particle population entering the plant remains within the validated domain (Pérez-García et al., 2020; Pérez-García et al., 2021; Rodvalho et al., 2025; Välikangas et al., 2025).

12.2 The MINESCALE decision gates

The synthesis of Sections 3–11 supports an eight-gate framework. The gates are sequential in logic but iterative in practice: failure at a later gate can force a return to feed definition, mechanism identification, or pilot design. The framework does not generate a universal numeric scale-up factor; it identifies whether the

evidence chain is mature enough to support the next engineering decision. Figure 4 presents the proposed MINESCALE decision-gate framework.

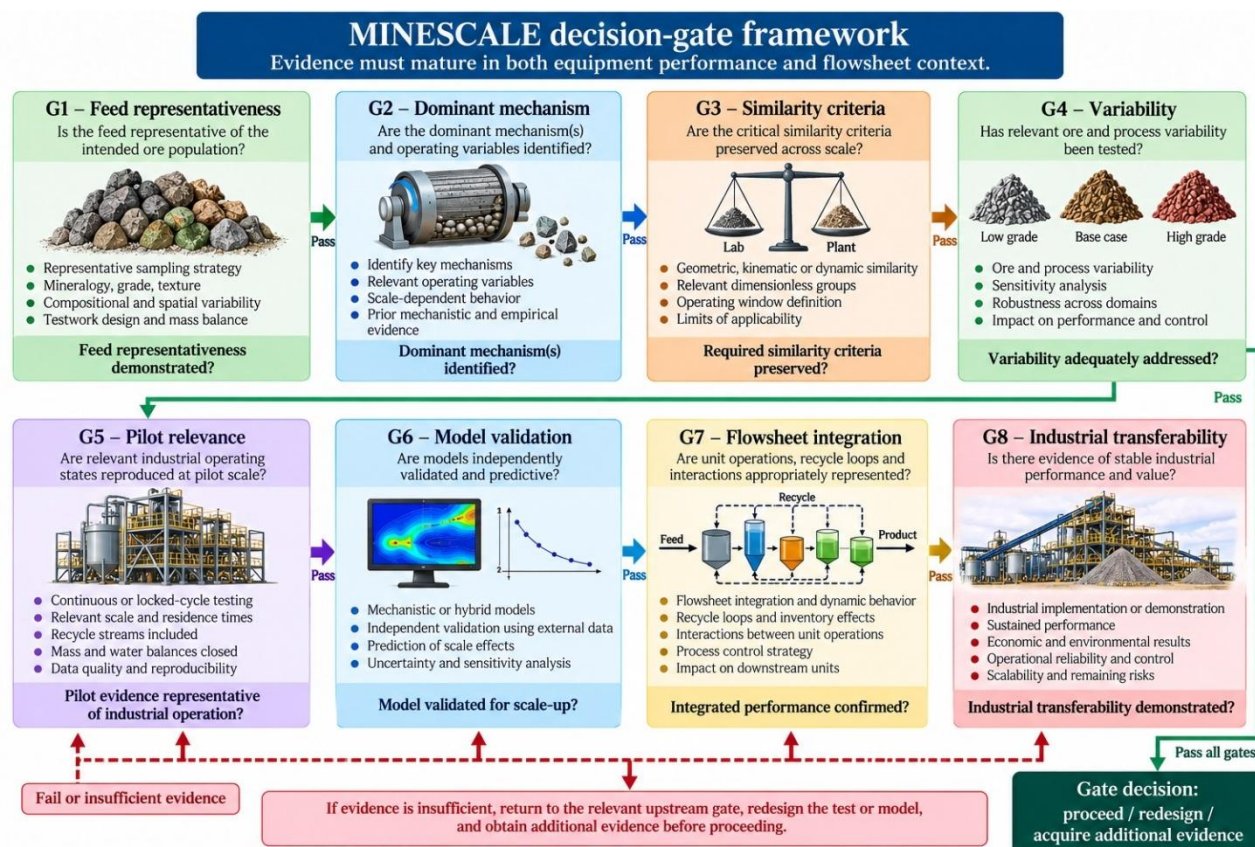


Figure 4. Proposed MINESCALE decision-gate framework

Note. Original synthesis by the author; conceptually adapted from staged testwork, commissioning, external model validation, digital twins, and uncertainty-propagation evidence (Contreras, 2025; de Jong, 2024; Lotter et al., 2024; Nad et al., 2022; Ohenoja et al., 2023; Quintanilla et al., 2025; Rodriguez et al., 2026; Välikangas et al., 2025).

A project should not proceed simply because a pilot achieved target recovery or throughput. The gate logic asks whether the feed was representative, whether the governing mechanism is understood, whether similarity criteria were identified, whether ore variability was challenged, whether pilot states were industrially relevant, whether the model was externally validated, whether recycles were represented, and whether commercial evidence exists. Table 9 defines the eight MINESCALE gates and the minimum evidence expected at each gate.

Table 9. MINESCALE decision gates and minimum evidence

Gate	Decision question	Minimum evidence	Action if evidence is weak
G1 — Feed	Does the test material represent process-relevant ore domains?	Sampling plan, mineralogy, PSD, liberation, rheology envelope	Redesign sampling/test matrix
G2 — Mechanism	Is the dominant performance mechanism identified?	Mechanistic hypothesis tied to measurable state variables	Acquire targeted diagnostics
G3 — Similarity	Which criteria must be preserved?	Defined similarity variables and unavoidable compromises	Change equipment/test protocol or model



G4 — Variability	Has the mechanism been challenged across ore variability?	Domain-based or statistically representative testing	Expand variability campaign
G5 — Pilot	Does the pilot reproduce industrially relevant states?	Continuity, RTD, inventory, recycle, and control relevance	Redesign pilot or add continuous testing
G6 — Model validation	Is prediction externally validated?	Independent dataset/scale and stated calibration domain	Do not extrapolate beyond evidence
G7 — Integration	Are interacting units and recycles represented?	Closed material/water loops or validated dynamic model	Expand system boundary
G8 — Industrial transferability	Is commercial performance demonstrated?	Industrial survey, commissioning, or sustained operating data	Apply risk allowance / staged deployment

Note. Proposed by the author from the critical synthesis of staged testwork, industrial validation, model adaptation, and uncertainty studies (Contreras, 2025; de Jong, 2024; Denzel et al., 2026; Lotter et al., 2024; Massinaei & Javanshiri, 2026; Nad et al., 2022; Ohenoja et al., 2023; Quintanilla et al., 2025; Rodriguez et al., 2026; Seppi et al., 2025; Sun et al., 2025; Välikangas et al., 2025; B. Zhang et al., 2025; M. Zhang et al., 2025).

The framework is intentionally conservative: it distinguishes a successful experiment from a transferable design basis. MINESCALE does not assign a universal numerical score. For retrospective appraisal, each gate is classified as Pass when direct evidence is reported, Conditional when evidence is partial or indirect, and Not demonstrated when the publication does not provide the information required for that gate.

12.3 Positioning MINESCALE relative to adjacent development frameworks

Table 10 compares MINESCALE with conventional equipment scale-up, TRL/stage-gate logic, and geometallurgical approaches.

Table 10. *How MINESCALE differs from adjacent scale-up and maturity concepts*

Dimension	Conventional equipment scale-up	TRL / stage-gate logic	Geometallurgy	MINESCALE
Primary question	How should unit size/capacity be extrapolated?	How mature is the technology/project?	How does ore variability affect process response?	Is the bench-to-industrial transfer evidence complete enough for the decision?
Feed representativeness	Often implicit	Not a primary criterion	Primary	Explicit G1
Mechanism/similarity	Primary in mechanistic methods	Usually indirect	Secondary	Explicit G2–G3
Ore variability	Often case-specific	Usually indirect	Primary	Explicit G4
Pilot industrial-state reproduction	Variable	Strong maturity signal	May be included	Explicit G5
Model validation	Method-dependent	Not necessarily required	Method-dependent	Explicit G6
Flowsheet recycles/interactions	Often outside unit boundary	Can be stage-specific	Can be represented	Explicit G7



Industrial transferability	Desirable but not always part of method	Primary at high maturity	May be available	Explicit G8
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Note. Qualitative author synthesis. The comparison clarifies scope rather than ranking competing frameworks. MINESCALE integrates feed, mechanism, variability, validation, and flowsheet evidence into one transferability sequence.

TRL and stage-gate approaches are valuable for technology maturity and project governance, while geometallurgy is indispensable for ore-domain definition. MINESCALE is positioned differently: it asks whether the particular evidence chain supporting a scale-transfer claim remains valid for a defined ore, equipment architecture, and flowsheet state. Its intended use is therefore complementary rather than competitive.

12.4 Retrospective stress test of MINESCALE

To examine whether the gates reveal differences among evidence architectures, we applied the framework retrospectively to six deliberately selected published scale transitions spanning integrated commissioning, mini-pilot-to-industrial flotation, industrial model validation, adaptive pilot modeling, industrial crusher modeling, and full-scale magnetic separation. The cases were selected to represent contrasting evidence architectures and are illustrative rather than statistically representative. This exercise is not a prospective validation of MINESCALE and does not convert the literature into a numerical ranking; instead, it tests whether the gates expose materially different evidence gaps in studies otherwise described as "validated" or "scaled up." Table 11 summarizes the resulting gate patterns, strongest evidence, reporting gaps, and interpretations for the six selected cases.

Table 11. *Retrospective MINESCALE stress test for selected cross-scale studies*

Published case	Gate pattern (G1→G8)	Strongest evidence	Main reporting gap	Interpretation
Kamoa-Kakula flowsheet/commissioning (Lotter et al., 2024)	P–P–C– C–P–C– P–P	Continuous mini-pilot linked to commissioning and integrated flowsheet evidence	Similarity and ore-domain challenge are incompletely reported	Strong integrated transfer; residual uncertainty is concentrated in variability/similarity reporting.
Imhoflot mini-pilot → industrial (Hassanzadeh et al., 2024)	C–P–P– ND–P– C–C–P	Direct mini-pilot-to-industrial equipment transition	Ore-domain challenge and full flowsheet closure	Strong equipment-scale transition; integrated-route transfer remains less explicit.
Industrial grinding PBM (de Jong, 2024)	C–P–P– C–ND– P–P–P	External validation against industrial grinding/classification data	No pilot-development sequence is reported	Strong model and industrial validation within the stated equipment/circuit boundary.
Adaptive pilot flotation digital twin (Ohenoja et al., 2023)	C–C–C– P–P–P– C–ND	Adaptive pilot model validated under changing feed conditions	Commercial-scale validation	Strong adaptive pilot evidence; industrial transfer remains untested.



Industrial jaw-crusher DEM (Rodriguez et al., 2026)	C–P–P– C–ND– P–C–P	Industrial survey validation of DEM/breakage modeling	Pilot sequence and integrated flowsheet evidence	Strong equipment/model evidence with a deliberately local system boundary.
Full-scale cHGMS (B. Zhang et al., 2025)	C–P–P– C–C–C– C–P	Full-scale commercial separator evidence	Complete feed-variability and integrated-route validation chain	Strong commercial hardware evidence; transferability beyond the reported application remains conditional.

Note. Gate pattern is reported in G1→G8 order. P = Pass: direct evidence reported; C = Conditional: partial or indirect evidence; ND = Not demonstrated in the cited publication. Ratings describe reporting against MINESCALE questions, not the inherent scientific quality of each study.

The stress test shows why "industrial" and "validated" should not be treated as binary labels. Kamoa-Kakula provides unusually strong integrated evidence because feed characterization, continuous mini-pilot balancing, and commissioning are connected. By contrast, industrial model-validation studies can be very strong at G2, G3, G6, and G8 while remaining intentionally weak at G5 or G7 because a pilot or integrated route was outside their scope. The framework therefore exposes the boundary of each claim without penalizing a study for questions it did not attempt to answer.

12.5 Limitations of the evidence base and research agenda

Several limitations constrain both the review and any general scale-up framework. First, unsuccessful scale-ups are underreported, creating publication bias toward technologies that reached pilot or commercial success. Second, industrial studies often rely on proprietary data and provide less detail on feed, control, residence time, or recycle than laboratory papers. Third, vendor-authored and single-site case studies can have high practical value but limited external generalizability. Fourth, the definitions of pilot, demonstration, and full-scale vary by technology, so equipment size alone cannot standardize evidence levels. Fifth, ore and mechanism heterogeneity precludes statistical pooling across unit operations.

The MINESCALE framework itself is a synthesis, not a prospectively validated decision rule. The retrospective stress test suggests preliminary discriminative utility by revealing materially different evidence gaps across the selected cases, but future work should apply the gates prospectively during project development and compare gate outcomes with subsequent commissioning performance. The framework should also be tested for inter-rater reproducibility so that different reviewers classify Pass, Conditional, and Not demonstrated consistently.

Four research priorities follow. More studies should document complete bench-to-continuous-laboratory-to-pilot-to-industrial sequences, including failed predictions. Ore variability should be explicitly embedded in scale-up test matrices and uncertainty analysis. Scale-up studies should report industrial state variables—RTD, effective volume, solids inventory, water chemistry, rheology, and control state—rather than only recovery and throughput. Finally, digital-twin and machine-learning studies should report out-of-sample and cross-scale validation so that predictive accuracy is not confused with transferability (Contreras, 2025; de Jong, 2024; Ghasemi et al., 2025; Käyhkö et al., 2022; Mancilla et al., 2025; Nad et al., 2022; Nobahar et al., 2026; Ohenoja et al., 2023; Quintanilla et al., 2025; Seppi et al., 2025; Välikangas et al., 2025; Zeb et al., 2024).

Full-scale magnetic-separation developments and industrially validated large-scale flotation columns show the value of explicitly publishing scale transitions. Comparable documentation remains sparse for cyclone clusters, material-handling bottlenecks, surge-capacity design, and integrated dewatering–water-recycle–flotation interactions, making these high-value targets for future work (Huang et al., 2026; Sun et al., 2025; B. Zhang et al., 2025).



13. CONCLUSIONS

Scale-up in mineral processing should be treated as an evidence-transfer problem rather than an equipment-enlargement problem. A scale transition is defensible only when the mechanisms controlling performance are preserved or explicitly modeled and when the test or model is challenged against a more industrially representative state.

Across unit operations, different mechanisms dominate. Comminution depends on breakage environment, energy, transport, and liberation; classification on partition behavior, pressure, water split, and regime transitions; physical separation on particle trajectories and field interactions; flotation on kinetics, hydrodynamics, and froth transport; dewatering on structure formation, rheology, permeability, and compression; and material handling on flowability, segregation, hydraulic margin, wear, and sustained availability. These differences preclude a universal scale-up factor.

Three boundaries recur across the evidence. Ore variability is the first because an unrepresentative feed invalidates otherwise rigorous testwork. Continuity is the second because RTD, inventory, recycle, and control appear when batch systems become continuous. Integration is the third because upstream and downstream units modify each other's boundary conditions through circulating loads, water chemistry, fines generation, availability, and control dynamics.

The proposed MINESCALE framework converts these findings into eight auditable gates: feed representativeness, dominant mechanism, similarity criteria, variability, pilot relevance, model validation, flowsheet integration, and industrial transferability. Retrospective application to selected published cross-scale cases suggests that the framework can distinguish strong equipment-level validation from stronger evidence of integrated transferability without forcing heterogeneous evidence into one numerical score, although prospective and inter-rater validation remain necessary.

The central research need is therefore not a better generic scale-up factor. It is a stronger evidence architecture for deciding when a scale-up relationship is valid, where it is valid, what uncertainty remains, and what must be revalidated when the ore, equipment architecture, control structure, or flowsheet changes.

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Conflict of Interest

The author declares no conflict of interest.

Data Availability

No new experimental datasets were generated. All quantitative values discussed in the review are traceable to the cited literature.

Author Contributions

Conceptualization, critical analysis, literature synthesis, visualization, and manuscript preparation by author.

Appendix A. Critical Cross-Cutting Search Strings

Table A1 reports the 20 cross-cutting Boolean strings used to interrogate the central thesis across unit operations. These strings complement the operation-specific search families developed for comminution,



classification, physical separation, flotation, dewatering, material handling, flowsheet integration, and digital models.

Table A1. Critical cross-cutting Boolean search strings

ID	Critical question	Boolean string
C1	Scale-up × variability	(geometallurgy OR geometallurgical OR "ore variability") ("mineral processing" OR beneficiation) ("scale-up" OR pilot OR "full scale" OR industrial) (performance OR recovery OR throughput)
C2	Scale-up × representativeness	(geometallurgy OR "metallurgical testwork" OR "mineral processing") ("representative sample" OR representativity OR "sample representativeness" OR "variability sample") (pilot OR "process design" OR "scale-up")
C3	Scale-up × mineralogy	("mineral processing" OR flotation OR comminution) (mineralogy OR "process mineralogy" OR mineralogical) ("scale-up" OR pilot OR industrial) (performance OR recovery OR throughput)
C4	Scale-up × liberation	(flotation OR comminution OR "mineral processing") ("mineral liberation" OR liberation) ("scale-up" OR "batch-to-plant" OR pilot OR industrial) (performance OR recovery)
C5	Scale-up × rheology	("mineral processing" OR grinding OR flotation OR thickening OR slurry) (rheology OR rheological OR viscosity OR "yield stress") ("scale-up" OR bench OR pilot OR industrial) (performance OR transport OR settling)
C6	Scale-up × hydrodynamics	(flotation OR hydrocyclone OR grinding OR "mineral processing") ("scale-up" OR scaling) (hydrodynamics OR turbulence OR "gas holdup" OR "energy dissipation") (pilot OR industrial OR "full scale")
C7	Scale-up × RTD	(flotation OR grinding OR "mineral processing") ("residence time distribution" OR RTD OR "effective residence time" OR "collection time") ("scale-up" OR pilot OR industrial OR plant)
C8	Scale-up × energy	(comminution OR grinding OR flotation OR "mineral processing") ("specific energy" OR "energy density" OR "power density" OR "energy dissipation rate") ("scale-up" OR pilot OR industrial) performance
C9	Scale-up × control	("mineral processing" OR grinding OR flotation) ("process control" OR "plant-wide control" OR APC OR "model predictive control") (industrial OR plant) ("scale-up" OR variability OR disturbance)
C10	Scale-up × recycle	("mineral processing" OR flotation OR grinding) (recycle OR recirculation OR "process water" OR "circulating load") (flowsheet OR circuit OR "plant-wide") ("scale-up" OR performance)
C11	Unit operation × flowsheet	("unit operation" OR comminution OR classification OR flotation OR dewatering) ("integrated flowsheet" OR "process integration" OR coupling OR interdependency) "mineral processing" (scale-up OR simulation OR validation)
C12	Bench × pilot	("mineral processing" OR flotation OR comminution) ("bench scale" OR laboratory) ("pilot scale" OR "pilot plant" OR "mini-pilot") (performance OR validation OR "scale-up")
C13	Pilot × industrial	("mineral processing" OR beneficiation) ("pilot scale" OR "pilot plant" OR "mini-pilot") ("industrial scale" OR "full scale" OR commercial OR commissioning) (performance OR validation)
C14	Bench × plant	("mineral processing" OR flotation OR grinding) ("bench-to-plant" OR "batch-to-plant" OR "laboratory-to-plant" OR "laboratory-to-industrial") (prediction OR validation OR performance)
C15	Mechanism × transferability	("mineral processing" OR flotation OR comminution) ("scale-up" OR transferability OR "scale transfer") (mechanism OR hydrodynamics OR kinetics OR RTD OR liberation OR rheology) (pilot OR industrial)

C16	Model × industrial validation	("mineral processing" OR beneficiation) (model OR simulation) ("industrial validation" OR "plant validation" OR "plant data" OR "production data" OR "plant survey" OR commissioning) ("scale-up" OR prediction)
C17	CFD × industrial	("mineral processing" OR flotation OR hydrocyclone OR grinding) (CFD OR "computational fluid dynamics") (industrial OR "full scale" OR demonstration OR field) (validation OR measurement OR survey)
C18	PBM × industrial	("mineral processing" OR grinding OR comminution) ("population balance model" OR PBM) (industrial OR "full scale" OR plant) (validation OR prediction OR survey)
C19	DEM × industrial	("mineral processing" OR crushing OR grinding OR HPGR) (DEM OR "discrete element method") (industrial OR "full scale" OR plant) (validation OR survey OR measurement)
C2	Digital twin × validation	("mineral processing" OR grinding OR flotation) ("digital twin" OR "digital twins") (pilot OR industrial OR plant) (validation OR adaptation OR "operational data" OR performance)

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