Received: 15 November 2025 | Revised: 10 March 2026 | Accepted: 4 April 2026

DOI: 10.1002/aic.70397

AIChE JOURNAL

PERSPECTIVE

Particle Technology and Fluidization

Challenges and enablers in fluidization technology

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Abstract

Gas–solid fluidized beds provide excellent heat and mass transfer for high-throughput operations from coating to catalytic conversion and underpin emerging low-carbon technologies. Yet industrial reliability, scale-up, and control lag scientific understanding, particularly as finer, stickier, and more variable feedstocks increasingly challenge conventional heuristics. This Perspective identifies five critical challenges: (i) small, cohesive, and/or irregular particles, (ii) complex chemistries and evolving materials, (iii) limited gas–solid flow predictability, (iv) low energy and material efficiency, and (v) safety. We then highlight five enablers to accelerate progress: (1) robust, time-resolved sensing; (2) mechanism-based assistance and mitigation methods; (3) high-fidelity multiscale models bridging particles to reactors; (4) AI-driven design, optimization, and control; and (5) closer academia-industry collaboration. Together, these advances can transform fluidization from an empirical art into a predictive, reliable platform for circular and low-carbon technologies.

KEYWORDS

artificial intelligence, gas-solid fluidised bed reactor, multiscale modeling, particle technology, scale-up and process design

1 | INTRODUCTION/MOTIVATION

Gas–solid fluidization has been implemented industrially for wide-ranging applications (from catalytic cracking to pharmaceutical coating to plastic recycling) for more than a century.[1] Its widespread use stems from distinctive advantages, including excellent gas–solids contacting, nearly isothermal operation, and high rates of heat and mass transfer.[2]

Despite the extended history and proven utility, operation, design and scale-up remain more an art than science. Compared with single-phase systems, fluidized beds continue to lag in long-term reliability, with post-start-up operability reportedly declining over the past decades.[3] A striking paradox underscores this gap: while advances in computational fluid dynamics, particle characterization, and measurement techniques have significantly augmented the understanding and predictive capability of fluidization behaviors, industrial monitoring and performance have not kept pace. The inherent complexity of gas–solid interactions resists first-principles-based description, hampering straightforward translation of laboratory-scale innovations to industrial-scale systems operating under economic and regulatory constraints.

Moreover, modern applications exacerbate this complexity. Fluidized beds are increasingly expected to handle fine cohesive powders (e.g., pharmaceutical particles below 10 μm), irregular and variable feeds (e.g., biomass, waste-derived fuels), and reactive or functionalized solids (e.g., oxygen carriers, advanced catalysts). These contemporary demands challenge the boundaries of conventional heuristics, exposing the inadequacy of rules-of-thumb and underscoring the need for fundamental advances in design, operation and predictability.

The urgency of global sustainability targets has placed renewed emphasis on fluidization technology, as fluidized beds underpin many emerging green processes, including bioenergy with carbon capture, chemical looping combustion, plastic upcycling, and hydrogen production from methane or ammonia. However, the promise of these technologies is hindered by unresolved issues of operability, efficiency, scale-up, and safety. Overcoming these obstacles motivates this perspective article, which seeks to identify the most pressing challenges in fluidization technology, elucidate why they persist, and highlight the enablers required to address them. By critically examining these enduring issues, we seek to offer insights to not only improve the reliability of current industrial processes but also unleash the full potential of fluidization in accelerating the transition toward sustainable energy systems and circular economies.

2 | BACKGROUND

Among unit operations, gas–solid fluidized beds play a unique role, enabling physical operations such as drying, coating, granulation, and cooling, as well as chemical processes where particles act as reactants, catalysts, or sorbents (Figure 1). Their excellent heat and mass transfer rates and continuous particle circulation make them indispensable across industries including chemical, pharmaceutical, energy, and materials.

The commercial era of fluidization began with Winkler's coal gasifier in 1922. A century later, fluidized beds remain vital yet challenging. Despite their apparent simplicity of suspending solids in a gas stream, fluidization exhibits complex, often unpredictable behavior—from bubbling and clustering to attrition and fouling. Consequently, design and operation have historically relied on empirical correlations, model tuning and pilot-scale testing rather than universal mechanistic principles.

While such approaches have served industry well, modern demands for precision, flexibility, and sustainability now expose their limitations. Pharmaceutical regulations require tightly controlled particle size and coating uniformity, while energy and chemical plants must handle variable feedstocks without compromising efficiency, safety, or environmental compliance. Fluidized beds are increasingly deployed in green technologies—including carbon capture, hydrogen production, and plastic upcycling—where irregular, variable, and/or reactive feeds exacerbate long-standing challenges.

Advances in experimental and computational tools are transforming how fluidized beds are analyzed and understood. High-resolution diagnostics, such as electrical capacitance tomography and positron emission particle tracking, provide unprecedented insights into gas–solid hydrodynamics.[5] Concurrently, CFD simulations and machine-learning methods enhance understanding, prediction, and operation.[6,7] These developments mark a steady shift from heuristic to science-based operation.

Nevertheless, translation from bench-scale to industrial practice remains slow, often taking more than 10 years.[4] Scale-up continues to be a bottleneck[8]: processes that perform well in the laboratory often fall short at pilot or commercial scale, revealing a persistent gap between academic research (typically focused on idealized systems) and industrial reality (e.g., impurities, variability, extreme conditions, safety, economics, global logistics). Additional complexity arises with nanoparticles, hybrid materials, and circular-economy applications, underscoring the need to revisit fundamental assumptions about hydrodynamics and scale-up, coupled with judicious use of emerging tools.

Fluidized beds thus sit at the intersection of tradition and transformation—time-tested yet facing growing demands in carbon management, resource-efficiency, and circularity. Accelerating progress will require combining advanced experimental, computational, and data-driven tools with renewed emphasis on fundamental physics and practical scalability. The following sections outline five critical challenges that exemplify these tensions and five opportunities for innovation. We recognize that such a selection of challenges and opportunities is, to some extent, subjective; nevertheless, we believe that this framework offers a useful and reasonably comprehensive picture of the field.

3 | CHALLENGING PHENOMENA

We present five critical challenges at intertwined but different scales (Figure 2). At the particle scale, increasingly smaller and more geometrically complex particles introduce significant processing difficulty, while complex chemical compositions, such as coatings or hybrids, further complicate operation. At the bed scale, these intrinsic particle properties manifest as limited predictability of flow behavior, with flowability often needing to be evaluated on a case-by-case basis. Finally, at the system scale, sub-optimal energy and material efficiency hamper sustainability and safety concerns (particularly those associated with nanoparticles and health). This structure underscores the multiscale nature of the challenges faced by modern fluidization technologies.

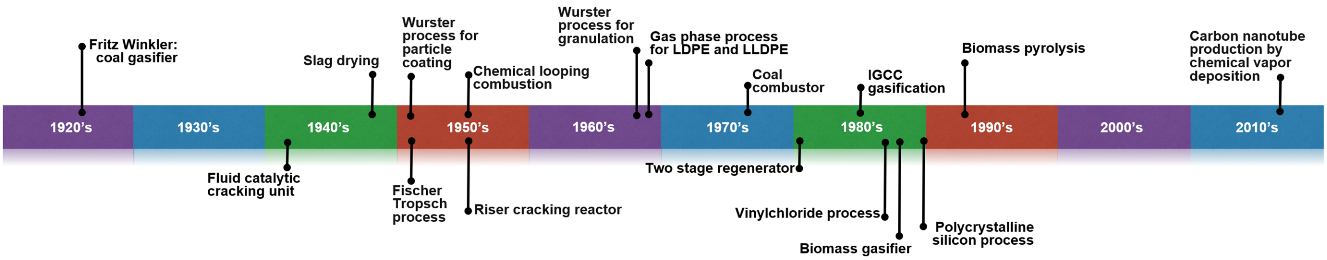

FIGURE 1 A timeline of fluidization applications, partly based on Cocco & Chew.[4] The vertical lines roughly indicate the introduction of a technology, typically at the pilot plant scale or small industrial scale. LDPE, low-density polyethylene; LLDPE, linear low-density polyethylene; IGCC, integrated gasification combined cycle.

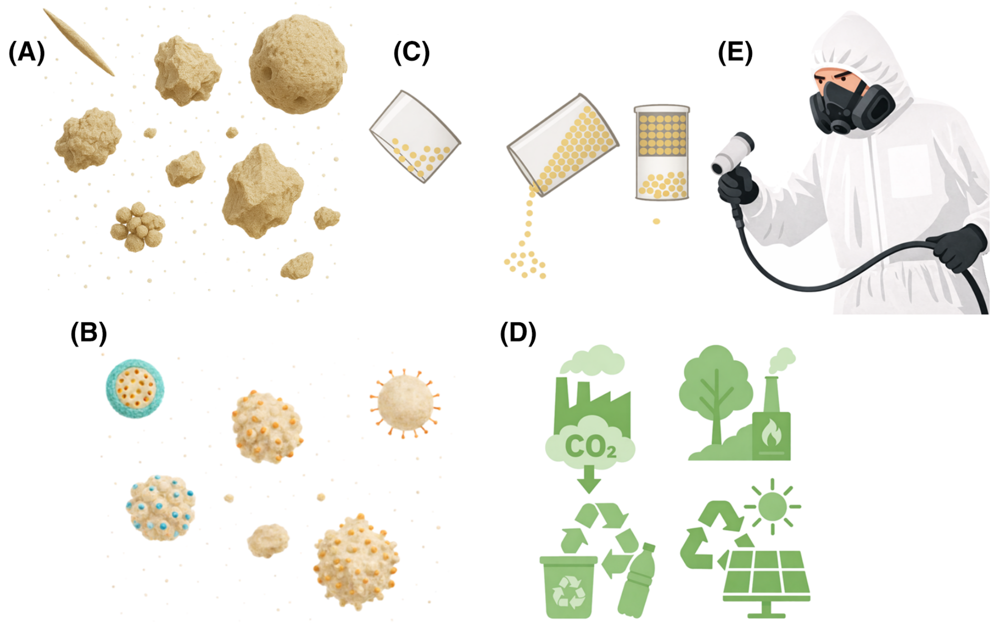

FIGURE 2 The five main challenges discussed: (A) physical particle properties, (B) chemical particle properties, (C) flowability, (D) sustainability, and (E) safety.

3.1 | Physical properties of advanced particles

In most of the early fluidized bed processes, the particles served as *supporting agents*, for example, inert sand in fluidized bed combustors or catalyst particles in fluidized catalytic reactors. This configuration allowed the particle size to be selected within a reasonable region of the Geldart chart (a widely used classification of fluidization behavior based on particle size and gas-particle density difference),[9] typically Groups A or B. However, when the particles themselves constitute the feedstock or final product, they may not fall into these more easily fluidizable Geldart Groups. In several modern applications—particularly in the food and pharmaceutical industries—particle diameters tend to be in the range of 1–20 μm, corresponding to Geldart Group C, which is difficult to fluidize because of dominant interparticle cohesion. The rise of nanoscience has further driven interest in processing even smaller particles, such as in the synthesis of core-shell nanostructures.[10] Generally, the smaller the particles, the stronger the role of agglomeration, which can negate the benefits of nanoparticles. On the other hand, green applications like biomass and plastic pyrolysis herald the need for fluidizing the larger Geldart Group D particles, which are often irregular in shape and sticky during the process.

The fluidization quality is governed not only by the mean particle size but also by the particle size distribution (PSD). In a seminal study, Grace and Sun[11] demonstrated that, for two particle batches with the same number-averaged diameter in a catalytic fluidized bed reactor, a broader size distribution yielded significantly higher conversion, which can be traced to more uniform axial temperature profiles.[12] Also, increasing the fraction of fine particles is well acknowledged to improve fluidization behavior, though elutriation can also be exacerbated. However, such adjustments to the PSD are more feasible when the particles act as enablers of the process (e.g., catalyst particles) than when they are the product itself.

Numerous other physical particle properties also play important roles. A key example is particle shape: the greater the deviation from sphericity (e.g., needle-like or flaky particles), the more difficult fluidization becomes. Another is surface roughness, which can be particularly influential for small particles, with surface asperities acting as spacers to prevent close contact and mitigate excessive agglomeration.

Importantly, in many applications, particle properties are not constant during operation. During fluidization, chemical reactions, thermal exposure, or mechanical stresses may induce changes such as melting, sintering, or attrition of the particles. Such dynamic evolution further complicates hydrodynamics, prediction, scale-up, and control.

3.2 | Chemical properties of advanced particles

The chemical composition of particles strongly influences their fluidization behavior. It affects several key physical properties, such as density, surface energy, and interparticle forces, as discussed in the previous section. For example, a surface coating or shell can alter the Hamaker constant, thereby modifying particle-particle interactions, particularly for Geldart Group A and smaller particles.

When catalyst particles are used to convert a gaseous reactant into a gaseous product, the particles generally remain chemically stable over time. This relative stability allows their composition to be optimized for process performance, for instance, to minimize unwanted side reactions and to show optimum fluidization behavior. In contrast, in processes wherein the particles themselves are the product, their chemical composition evolves dynamically. In polymerization reactors, for example, polymer chains grow on tiny catalyst seeds as monomers such as ethylene or propylene polymerize, forming much larger granules. During this process, uncontrolled growth due to high reaction rates, heat release, or electrostatic effects must be avoided, as it can lead to sheeting or chunking, which can eventually result in an unscheduled shutdown. Similarly, in food and pharmaceutical manufacturing, particles are granulated or coated by spraying with a binder or coating liquid, and the process must be carefully controlled to prevent excessive particle agglomeration.[13]

A particularly interesting class of materials produced in fluidized beds are core–shell particles, which serve diverse purposes. In catalysis—where they are often referred to as egg-shell catalysts—the expensive active material is deposited near the surface to maximize cost-effectiveness, as diffusion limitations can prevent reactants from reaching the particle core. In pharmaceuticals and food, coatings can be designed to control dissolution rates or achieve delayed-release functionality. In energy materials, such as Lithium-ion battery cathode particles, thin protective surface films can enhance lifetime and stability. While such coatings are often applied via liquid-phase processes, gas-phase coating techniques with higher precision are being actively developed.[14]

Fluidized beds also underpin energy conversion and carbon management technologies in which particles undergo chemical transformation. Classical examples include fluidized bed combustion and gasification, where solid fuels such as coal or biomass react within an inert bed material, typically sand. More recently, chemical looping processes using oxygen carriers have gained interest for integrated CO_2 capture.[15] Research efforts are also exploring metal-fueled systems, where iron particles act as recyclable solid fuels, and solar-driven fluidized beds, where particles absorb and store thermal energy to drive thermochemical reactions.

3.3 | Flowability & fluidization quality

The physical and chemical properties of particles strongly influence both their flowability and fluidization quality. Flowability is commonly characterized by the angle of repose, defined as the steepest angle at which a particle pile remains stable without collapsing. Fluidization quality, on the other hand, is often quantified by the normalized pressure drop, that is, the ratio of the measured pressure drop to the theoretical value assuming all particles are fully supported by the gas flow. Although good flowability generally correlates with higher fluidization quality, the relationship is not definitive.[16]

With respect to particle size, Geldart Groups A and B are known to fluidize most effectively. Introducing a fraction of fine particles, thereby broadening the PSD, can often enhance fluidization behavior. Interestingly, very fine or submicron particles may sometimes fluidize better than expected due to agglomerate formation; these agglomerates behave as larger, composite entities whose effective properties fall within the Geldart A or B Groups.

When particles are sticky (i.e., tending to adhere after collisions), fluidization quality deteriorates sharply. Even non-sticky particles can exhibit a sudden transition to cohesive behavior when humidity or temperature increases. The chemical composition of the particles plays a key role in determining the threshold for this transition. Another major factor affecting fluidization performance is electrostatics. Electrostatic charging, or tribocharging, arises primarily from particle-particle and particle-wall collisions; the former being dominant since the total particle surface area far exceeds that of the reactor walls. Although collisions between different materials are the principal source of tribocharging, interactions between particles of the same material but different sizes can also generate charges.[17]

In general, excessive interparticle forces, including van der Waals attraction, liquid bridging, and electrostatic interactions, can lead to severe agglomeration and even defluidization. To mitigate these effects, one can either reduce the strength of these forces (e.g., by adjusting temperature) or employ fluidization-assistance techniques (see Section 4.2).

3.4 | Sustainability

Fluidized beds offer significant potential for clean energy and circular waste processing, encompassing bioenergy with carbon capture and storage (BECCS), hydrogen production, and waste-to-fuel conversion. Notably, BECCS enables negative emissions by coupling biomass combustion with CO_2 capture, though large-scale deployment remains limited by feedstock logistics and lifecycle considerations.[18,19] Similarly, fluidized bed gasification provides a versatile route to hydrogen and syngas from biomass and waste, continually enhanced by advances in hydrodynamic modeling and reactor optimization.[20] Fluidized-bed systems are also progressing toward demonstration scale for CO_2 capture technologies, such as chemical looping combustion (CLC), calcium looping, and oxy-fuel fluidized-bed combustion, supported by an expanding body of techno-economic and life-cycle assessments.

Despite this promise, feedstock variability remains a critical barrier. Biomass's high volatile content can lead to unburnt emissions, while its alkali-rich ash (e.g., potassium) drives sintering, agglomeration, and eventual defluidization.[21] Also, waste-derived fuels introduce heavy metals and chlorine, accelerating fouling, corrosion, and toxic emissions.[22] Addressing these issues demands robust reactor designs, advanced sorbents, and durable materials capable of operating under harsh conditions.

Technical and material challenges hinder broader adoption. Fluidization dynamics remain complex, and empirical-based design approaches continue to limit reactor reliability and scalability.[8] CLC exemplifies both potential and difficulty (e.g., alkali-induced agglomeration, sulfur poisoning, sluggish char conversion).[21] Novel functional materials (e.g., oxygen carriers, catalysts) must resist attrition and deactivation, while safety risks from nanoparticle emissions and dust explosions require ongoing attention.

Economic and scale-up challenges also pose formidable hurdles. Transitioning from laboratory to industrial scale can take over a decade,[8] a timeline incompatible with climate imperatives. Industrial conservatism – favoring gradual, multi-stage scaling to mitigate risk – delays deployment of sustainable technologies. Emerging tools, including hybrid models, digital twins, and AI-driven designs, could reduce development time by about 40%,[8] yet remain underutilized. Early large-scale demonstrations of green fluidized-bed systems (e.g., CLC for carbon capture) still depend heavily on policy support through carbon pricing, co-funding, or risk-sharing mechanisms.

In summary, the sustainability potential is tempered by the challenges of feedstock heterogeneity, material durability, process complexity, and slow scale-up. Overcoming these barriers will require several innovations, which will be discussed later in this article. If these advances materialize, fluidized beds could evolve into predictable, efficient, and sustainable process platforms, anchoring the transition to a low-carbon and circular economy.

3.5 | Safety

Fluidized beds often operate under harsh conditions (e.g., high temperatures, elevated pressures, and chemically aggressive environments), requiring strict safety measures. Apart from the "standard" risks playing a role in chemical processes, there are three important phenomena typical for fluidized beds (and certain other particle operations):

- Erosion: Continuous particle motion and frequent collisions with walls or internals can cause erosion, leading to wall leakage or damage to internals such as heat-exchanger tubes and sensors.
- Dust explosions: The large surface area and dispersed nature of fluidized particles can trigger dust explosions.[23]
- Electrostatics: Frequent particle-particle collisions induce triboelectric charging, especially at temperatures below 50°C.[24] Such charge accumulation may cause ignition, though the electrostatic charging phenomenon remains highly unpredictable.[25]

In pharmaceutical and food processing, where fluidized beds are used for drying, coating, and granulation, contamination control is also critical. Strict cleaning procedures are required—particularly in batch operations—to prevent cross-contamination. Equipment should be designed to avoid dead zones where material may accumulate and degrade, compromising product quality and safety.

The exhaust gas stream from a fluidized bed typically contains both gases and fine solid particles (dust). Depending on composition and local regulations, it must be treated (e.g., remove some gas component and/or particles) before discharge. Gas cleaning may involve sorbents, scrubbing, or reactive treatments, while fine solids are typically removed using cyclones, fabric filters, electrostatic precipitators, or their combinations.

Summarizing, fluidized beds have a number of specific aspects that should be considered to ensure safe operation.

4 | ENABLERS TO BE DEVELOPED

Addressing these challenges requires accelerated development and deployment of five key enablers (Figure 3), each with distinct limitations yet high transformative potential. First, advanced sensors and measurement techniques are needed to deliver real-time, high-fidelity insights into fluidized-bed hydrodynamics, improving both understanding and operability. Second, assistance and mitigation strategies, such as vibration, acoustic excitation, or optimized gas distribution, can markedly enhance the fluidization of cohesive or irregular particles. Third, multiscale modeling frameworks that bridge particle-scale physics and reactor-scale performance will strengthen predictive capability and guide efficient, reliable design. Fourth, integrating artificial intelligence can accelerate progress across data analysis, experimental design, process optimization, and control. Fifth, closer academic-industrial collaboration is essential to align research with operational needs and translate fundamental advances into robust, scalable technologies.

4.1 | Sensors and measurements

The nature of fluidized beds makes accurate sensing and measurement challenging. First, their opacity severely limits the applicability of optical techniques. Second, they present a harsh environment—often involving high temperatures, aggressive chemicals, and rapidly moving, abrasive particles—which can quickly damage or erode sensitive sensors. As early as 1999, Werther[26] noted that, in industrial fluidized beds, only pressure and temperature were routinely measured. More than two decades on, this observation largely still holds.

In academic research, a range of tomographic techniques is widely used to visualize gas–solid flow structures. These methods allow the voidage distribution within a horizontal cross-section (or even an entire volume segment) of a fluidized bed to be visualized, often with respect to time. Electrical capacitance tomography is among the most common ones, though it offers relatively low spatial resolution. On the other hand, X-ray and γ-ray tomography provide much higher spatial resolution but require expensive equipment and extensive safety measures. Tomographic imaging in industrial-scale units is generally limited to column diameters up to about 1 m, such as in pharmaceutical applications,[27] but remains impractical for larger scale systems with diameters of several meters.

To understand mixing and residence time distribution in fluidized beds, tracer techniques are often employed, applicable to either the particle phase or the gas phase. Examples include radioactive or magnetic tracer particles, which can be detected externally, and radioactive gases or gases with detectable properties, such as helium, which can be monitored through changes in thermal conductivity. However, tracer methods are only sporadically used in industrial operations, primarily due to complexity, cost, and regulatory constraints.

Another promising direction is the use of soft sensors (or virtual sensors), which rely on relatively simple physical sensors combined with advanced data analysis or machine-learning algorithms.[28] For instance, high-frequency (400 Hz) pressure measurements have been successfully used to provide early warning of agglomeration in fluidized beds.[29] Even low-frequency 0.5 Hz pressure data have been tied

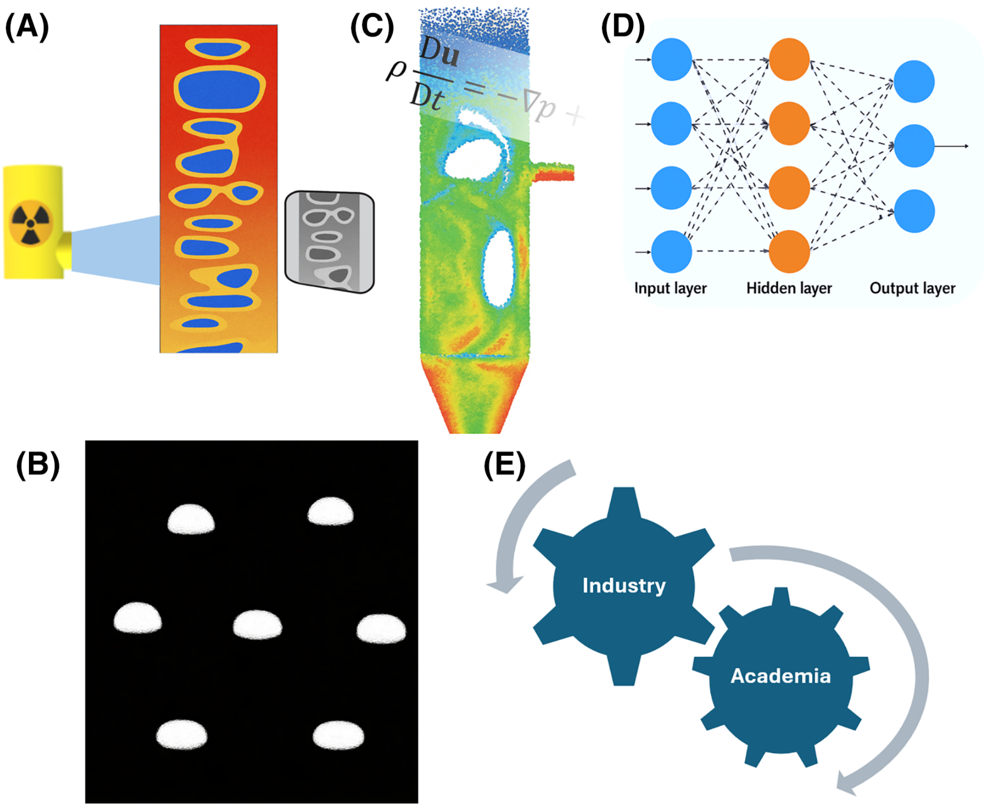

FIGURE 3 The five enablers discussed: (A) sensors & measurements, (B) assistance methods, (C) multiscale models, (D) artificial intelligence, and (E) academia-industry collaboration.

to fluidization quality.[30] Similar approaches have been demonstrated for moisture content estimation in fluidized-bed dryers and NO_x emission monitoring in fluidized-bed boilers.

4.2 | Assistance methods

There are three key reasons to apply assistance methods to fluidized beds: (i) increase process efficiency, (ii) enable fluidization of particles that otherwise fluidize poorly, and (iii) facilitate supplementary or intensified functionality. While in some cases this only leads to a modest change in the fluidization behavior, in other cases these approaches actively modify the prevailing fluidization regime, for example through dynamic forcing (e.g., vibration or oscillating the gas flow). It is non-trivial to cover all these methods from modest changes to drastic modifications by a single term; we have chosen to use "assistance methods" for lack of a better term.

Van Ommen et al.[31] reviewed four assistance methods designed to structure fluidized beds and achieve greater control over bubble size and distribution. Such structuring can enhance conversion and selectivity, and may also simplify scale-up by promoting more uniform bubbling behavior. The first method involves oscillating the gas flow. In very shallow or quasi-two-dimensional beds, this confers a completely regular bubble pattern.[32] In conventional three-dimensional beds, the effect is less pronounced but can still be beneficial for reducing bubble size variability. The second method is to improve gas distribution—both radially and axially—by using a fractal injector, ensuring a more homogeneous flow pattern. The third method focuses on controlling interparticle forces by polarizing the particles using an electric field. Although similar effects can be achieved using magnetic fields, electric fields are generally more energy-efficient. The fourth method involves optimizing the particle size distribution, since introducing a fraction of fine particles tends to reduce average bubble size.

For strongly cohesive materials, such as submicron powders, assistance methods are often essential to achieve proper fluidization and to prevent channeling or defluidization. Mechanical vibration, typically applied at frequencies around 50 Hz, is one common approach. Mechanical stirring can also be employed, though stirrer designs developed for liquid systems are usually not optimal for powders and must be adapted accordingly. Other techniques include the use of sound waves, though their scalability remains limited, and centrifugal fields, which require a fundamentally different reactor design rather than a simple retrofit. Additionally, microjets can generate localized zones of high gas velocity, effectively breaking down agglomerates and improving bed homogeneity.[33] There is no strict distinction between methods used for bed structuring and those for facilitating fluidization of cohesive materials; for instance, oscillating gas flow and electric fields have been successfully applied in both contexts.

Finally, certain assistance techniques aim to introduce additional process functionality, representing forms of process intensification. Examples include fluidized bed opposed jet mills, where particle grinding occurs simultaneously with fluidization, and fluidized-bed membrane reactors, in which membranes are integrated to add reactants or selectively remove products.[34]

4.3 | Multiscale models

Accurate predictive simulation of industrial-scale fluidization remains a major challenge.[35] Fluidization is inherently multiscale: reactor-scale performance depends on mesoscale structures (e.g., bubbles, clusters) emerging from microscale gas-particle and particle-particle interactions. These mesoscale structures strongly influence mixing, heat and mass transfer, and reaction rates, yet resolving them at industrially relevant particle numbers is computationally prohibitive. This scale disparity has led to a hierarchy of modeling approaches that balance computational tractability with physical fidelity.[36] Hybrid multiscale frameworks have also been developed, such as high-fidelity simulations on small domains informing coarse-grained models, and physics-constrained data-driven methods improving sub-grid closures.[6]

At the highest resolution level, particle-resolved direct numerical simulations (PR-DNS) resolve the boundary layer and fluid dynamics around individual particles, providing first-principles insight into interphase forces and mesoscale formation. Although restricted to small domains, they are useful for developing and refining closures for larger-scale models.

At intermediate resolution, Eulerian–Lagrangian approaches (CFD-DEM) track individual particles while solving the gas phase on a continuum grid. They resolve local particle interactions but are typically limited to laboratory or pilot scales due to computational cost. Coarse-grained variants such as multiphase particle-in-cell (MP-PIC) reduce cost by tracking parcels representing many particles and modeling particle stresses and collisions statistically.[37] Also, drag formulations have been further refined.[38]

At the reactor scale, Eulerian–Eulerian two-fluid models (TFM), which treat gas phase and solids phase as interpenetrating continua, are the primary workhorses. While their efficiency makes them suitable for industrial scales, predictive accuracy depends heavily on constitutive closures (e.g., drag laws, solids stress) that often require ad hoc tuning. Filtered two-fluid models (fTFM) reduce cost for fine-grid TFM by incorporating sub-grid corrections to represent unresolved mesoscale heterogeneity. Increasingly, data-driven approaches have been employed for developing closures trained on PR-DNS to improve continuum interphase forces,[39] as well as for adaptive meshing that balances accuracy and cost.[40]

Overcoming computational barriers also relies on higher-performance computing. GPU-accelerated CFD-DEM simulations can now handle on the order of 10^7 particles with heat transfer,[41] emerging exascale architectures allow for industrial-scale reactive fluidized bed simulation on the order of 10^9 computational cells,[42] while quantum computing has shown promise in enabling logarithmic scaling with system size.[43]

Industrial fluidized-bed reactors contain on the order of 10^{12}–10^{15} particles, remaining beyond current capabilities. Judicious integration of physics-data hybrids to bridge scales and advanced computing infrastructure appears poised to define the next generation of predictive fluidization models.

4.4 | Artificial intelligence and digitalization

Machine learning (ML), which is a subset of AI in which models learn relationships from data, offers powerful complements to traditional approaches by uncovering patterns in high-dimensional data that conventional methods often miss. Although ML applications in process systems engineering date back to the 1960s,[44] and the application to fluidized beds to the 1990s,[45,46] only recent advances in data availability, computation, and model architectures have enabled their effective application to fluidized systems. Data-driven tools provide new insights into mesoscale flow structures (e.g., bubbles, clusters) and cohesive interactions, while diagnosing challenges such as channeling, agglomeration, and efficiency loss.

AI is accelerating reactor design and optimization by replacing slow, trial-and-error scale-up with data-driven, adaptive workflows.[4] ML enhances early-stage design by identifying the most informative test conditions, reducing experimental effort without compromising statistical confidence. Generative and optimization-driven AI tools, such as Siemens HEEDS and hybrid search algorithms, rapidly explore thousands of reactor and distributor geometries, optimizing gas distribution, pressure drop, and particle residence times much faster than conventional experimental or CFD-based parametric studies. ML-based flowsheet synthesis and risk assessment models further accelerate scale-up by predicting operability limits and identifying process bottlenecks. Reinforcement learning (an ML framework in which an agent learns a control policy to maximize cumulative reward) further enables intelligent control, autonomously optimizing, for example gas injection.[47]

Digitalization extends these capabilities to real-time monitoring and control. Digital twins (computational replicas of physical systems updated in real time using sensor data) integrate sensor data with reduced-order or data-driven models to reconstruct flow fields and improve operation. For instance, Li et al.[48] combined enhanced sensing with temporal convolutional networks to create a circulating fluidized-bed digital twin that predicted hydrodynamics 25,000 times faster than CFD simulations with <20% error. Such systems enable adaptive control, fault detection, and energy optimization, marking a shift toward self-learning, predictive fluidization technology.

Despite prolific academic progress, industrial adoption of AI/ML in fluidized-bed systems remains limited. The most mature applications involve data-driven monitoring, soft sensors (inferential estimators of unmeasured variables), and decision-support tools that augment human operators. In contrast, fully autonomous reactor design, optimization, or plant-wide digital twins remain emerging practices, often limited by data availability, integration complexity, regulatory requirements, and safety considerations.

Finally, physics-aware ML,[49] which embeds governing equations and conservation laws into data-driven architectures, offers interpretable, generalizable models that refine constitutive equations and closures. Together, AI/ML and digitalization promise to transform fluidization from empirically tuned experimentation into a predictive, adaptive, and intelligent engineering discipline. Progress will depend on developing interpretable AI frameworks, curating high-quality open datasets, and advancing hybrid physics-data approaches that generalize reliably across particle types, scales, and operating regimes.

4.5 | Academia-industry collaboration

Merrow observed in the 1980s that, while many chemical processes scaled successfully to industrial scales, plants handling solid particles consistently underperformed; this gap was attributed to a misaligned R&D focus.[50] Specifically, industry prioritized chemical kinetics while paying less attention to fluidization physics, and the disparity in their characteristic length and time scales inevitably led to persistent gaps. In response, academics were spurred to investigate fundamental gas–solid hydrodynamics, delivering a range of advances, including better bubble behavior models and improved scaling methodologies. The broader lesson is discipline-independent: when academic research is aligned with real industrial pain points, and experimental and modeling tools are further improved, industrial progress accelerates dramatically.

Ideally, industrial feedback should steer academic research toward the most pressing needs (e.g., particle attrition, poor gas distribution, unreliable scale-up). For instance, if defluidization plagues biomass reactors, practicing engineers can direct academics to investigate gas distributor design, particle mixing strategies, or predictive sensing, ensuring research addresses root causes of operational hurdles rather than offering ad hoc remedies. Importantly, this does not imply abandoning first-principles research. Historically, it has been demonstrated that sustained investment in fundamental research in industrial R&D can generate profound technological and economic impact. Re-establishing such long-term perspectives remains critical for fields like fluidization. Such collaboration benefits both sides: academics gain access to real-world data and testbeds, while companies gain early insights into tailored solutions. The Technology Vision 2020 roadmap for the U.S. chemical industry, a joint effort of industry, government and academia, exemplifies this synergy.[51] By defining shared long-term R&D priorities and fostering collaboration, it helped shape significant advances in the chemical and process industries (e.g., multiphase modeling).

Despite these benefits, collaboration is not without trade-offs. Firms with high technological generality (i.e., technologies with broad applicability) gain greater economic benefits from direct academia-industry collaborations, whereas firms with high technological originality (i.e., highly novel or innovative technologies) experience smaller or marginal additional gains from such collaborations.[52] Moreover, the relationship between collaboration and scientific performance follows an inverted U-curve: initial boosts give way to diminishing returns as industrial pressures encroach on academic rigor.[53] Beyond these structural constraints, effective partnerships also depend on supportive funding and incentive structures. While fundamental research in fluidization is critical for reliable scale-up and industrial competitiveness, it may not always align with prevailing funding priorities or appear immediately transformative. Consequently, some challenges are addressed in-house within companies, driven by intellectual property considerations or short-term operational pressures. Bridging this gap requires sustained commitment from funding agencies and industry stakeholders to recognize the long-term industrial, economic, and societal value of fundamental advances in this established yet evolving field. An additional crucial role of academia is in educating future engineers and upskilling practicing engineers.

To maximize impact, partnerships can redefine success metrics (e.g., favoring scale-up efficiency or production yield alongside publications) while navigating legal frameworks. When balanced wisely, academia-industry collaboration remains a powerful enabler to advance fluidization technology where it matters most: in tackling global challenges.

5 | CONCLUSION AND OUTLOOK

A century after its industrial debut, fluidization technology remains both indispensable and enigmatic. Its ability to handle particles in a dynamic, fluid-like state has enabled advances across traditional and emerging industries. Yet the same features that make fluidized beds versatile—intimate gas–solid interactions, sensitivity to particle properties, and rich hydrodynamics—also underpin their persistent challenges. Despite progress in modeling, diagnostics, and process intensification, operability and predictability still lag single-phase systems.

The challenges outlined here stem from a convergence of longstanding limitations and new sustainability-driven demands. Fine, cohesive, and multifunctional particles push operations beyond conventional heuristics, while heterogeneous, variable, and impurity-laden feedstocks amplify agglomeration and defluidization risks. Meeting the demands for safer, greener, and more efficient processes requires rethinking scale-up, measurement, and control strategies.

Several pathways offer promise. Advanced sensors and real-time diagnostics—from tomography to soft sensing—must transition from laboratories to industry, enabling proactive control rather than reactive troubleshooting. Assistance methods, such as vibration, acoustic fields, and optimized gas distribution, should be integrated with materials design, ensuring that particle engineering complements process performance. Multiscale modeling can bridge particle-scale physics and reactor-scale operation, while AI and ML stand to accelerate design, optimization, and control through data-driven insights and reduced experimental trials. Above all, closer collaboration between academia and industry is crucial to align research priorities with operational needs and to de-risk first-of-a-kind commercial demonstrations.

Together, these developments mark the path toward transforming fluidization from an empirical art into predictive science. This transformation is essential if fluidized beds are to fulfill their role in the low-carbon transition, driving technologies such as carbon capture, hydrogen production, and circular chemical recycling. The coming years will determine whether the field continues along an incremental path or evolves into an even stronger cornerstone of sustainable industrial practice.

AUTHOR CONTRIBUTIONS

Jia Wei Chew: Conceptualization; writing – original draft; writing – review and editing; visualization; investigation; methodology. **J. Ruud van Ommen:** Conceptualization; writing – original draft; writing – review and editing; visualization; investigation; methodology.

CONFLICTS OF INTEREST STATEMENT

None of the authors have a conflict of interest to disclose.

DATA AVAILABILITY STATEMENT

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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How to cite this article: van Ommen JR, Chew JW. Challenges and enablers in fluidization technology. *AIChE J*. 2026;e70397. doi:10.1002/aic.70397