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Review

# Perspectives for artificial intelligence in bioprocess automation

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Recent advances in artificial intelligence (AI) have rapidly changed the lab automation landscape, promoting self-driving laboratories (SDLs) that enable autonomous scientific discovery. These trends are increasingly applied in bioprocess development, yet bioprocessing faces unique challenges — biological complexity, regulatory and safety requirements, and multiscale experimentation — that distinguish it from other automation domains. Rather than pursuing full autonomy, we foresee that hybrid SDLs, combining AI-driven decision-making with sustained human oversight, represent the most practical near-term trajectory. This review examines three interconnected perspectives: (i) hybrid human–machine decision-making for bioprocessing; (ii) laboratory design considerations in the era of AI; and (iii) scale-up challenges when transitioning from screening to manufacturing. We highlight critical gaps in data standardization and the required community efforts necessary to realize autonomous bioprocess innovation.

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## The race toward an artificial intelligence scientist? — the role of artificial intelligence for self-driving labs

Research on artificial intelligence (AI) is increasingly perceived as a key enabler of scientific discovery [1], transitioning from offline modeling toward systems steering experimental effort in real time. In chemistry and materials science, autonomous experimentation has accelerated closed-loop discovery [2,3]. Within the life sciences, landmark studies such as AlphaFold for protein structure prediction [4] or the discovery of the novel antibiotic halicin via deep learning [5] highlight the transformative power of AI. However, bioprocess engineering faces unique challenges regarding AI, including biological complexity, legal and regulatory requirements, and high variability and uncertainty in experimental setups.

Complementing AI advances, laboratory automation has matured from stand-alone unit operations (e.g. sample preparation) to whole ecosystems of interconnected devices in biofoundries. These industrial and academic facilities combine robotics, high-throughput analytics, and integrated data systems to implement the design-build-test-learn (DBTL) cycle [6]. Coordinated through initiatives like the Global Biofoundries Alliance [7], such laboratories demonstrate the potential of standardized, automated experimentation to accelerate bioprocess development.

The combination of AI and laboratory automation ultimately results in the concept of the self-driving lab (SDL): a system that combines robotics for automated experiments and data collection with AI systems that use these data to design, execute, and interpret experiments in closed loops [8]. An important stepping stone toward functional SDLs is the fusion of lab automation with large language models (LLMs) and other tools in agentic frameworks (e.g. *Coscientist* [9] and *ChemCrow* [10] in chemistry), which are able to translate high-level goals into executable plans, navigate documentation, and orchestrate whole experimental workflows.

In light of such advances, it is timely to raise the question: how much autonomy do we actually want in bioprocess automation? Following established autonomy levels for SDLs [8,11], complexity spans from Level 0 (no autonomy) through Level 1 (research assistance), Level 2 (partial autonomy), Level 3 (conditional autonomy), Level 4 (highly-autonomous research), to

Level 5 (AI scientist). Currently, most bioprocess automation operates at Levels 1–2 with significant human oversight, as bioprocesses involve complex multiscale experimentation, high experimental uncertainty, safety considerations, and regulatory requirements. The optimal balance between autonomy and human decision-making, therefore, needs to be discussed for future bioprocess applications.

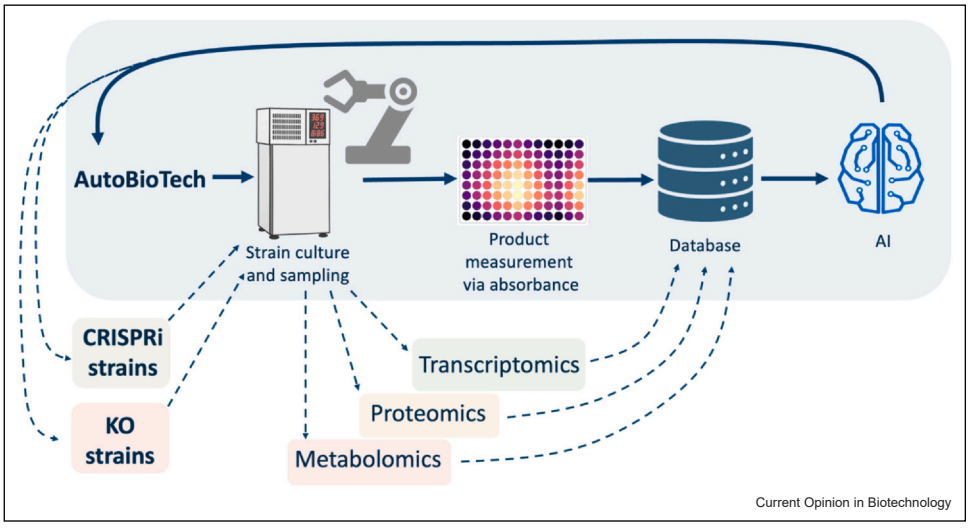
This review examines three interconnected perspectives: (i) hybrid human–machine decision-making for safe, regulated bioprocessing; (ii) laboratory design considerations as AI transforms infrastructure requirements; and (iii) scale-up challenges that distinguish bioprocess SDLs from their chemistry counterparts when transitioning from laboratory screening to manufacturing.

## Hybrid lab: human and machine decision-making for automated experimentation

While SDLs promise throughput and reproducibility that are unattainable by humans, full autonomy is not always feasible or practical for a range of reasons. First, a scientific process may not be automatable, the cost may be prohibitive [12], or the demand for the process may be too infrequent to justify the cost. Even if these requirements are met, the automation and robotics skills required may not be available in a standard biological lab. Finally, safety concerns may not advocate full autonomy: for example, an unattended SDL increasing virus pathogenicity [13–15] or producing a controlled substance drug [16] are scenarios that, while still unlikely, need to be avoided.

Hence, we anticipate that future SDLs will mostly take a hybrid form, in which human and AI/robotics components will intertwine not only for physical (e.g. experiments) and computational (e.g. data analysis) tasks, but also in the conception and design of studies. We expect these hybrid systems to be focused around one or more *core processes* that exhibit a full (or high) degree of automation (autonomy Levels 3–5), where benefits outweigh costs (see an example in Figure 1). Around these core processes, *auxiliary processes* with varying degrees of automation (including totally manual ones, autonomy Levels 1–2) would be flexibly coupled in a modular fashion. These processes are sparingly needed and can be eliminated, added, or modified (e.g. by upgrading to a core process) as required, without affecting the performance of the core processes. This approach permits the testing of modules before fully coupling them to core processes, as well as a flexible configuration that can be easily adapted to new requirements. The hybrid system also aligns with current developments in modular manufacturing [17,18].

**Figure 1**




Illustrative example of a possible hybrid automated lab in metabolic engineering. This hybrid lab example is composed of three fully automated core processes (in blue) and five auxiliary processes (in green, orange, and red). The core processes involve the generation of strains harboring different combinatorial pathways through the use of the fully automated AutoBioTech strain construction platform [31], the culturing of those strains, sample acquisition, and the measuring of the final production through absorbance. Data are then stored in a database for an AI to decide how to proceed next. Attached to these three core fully automated processes, we can see several auxiliary processes (green, orange, and red) displaying different levels of automation: from highly automated (green) to some automation (orange) or purely manual (red). A second and third alternative to build strains involves producing strains with downregulated genes through CRISPRi (e.g. as in Carruthers et al. [32]), or manually knocking genes out. Alternative ways to phenotype the strain involve transcriptomics, proteomics or metabolomics. These data need not be collected in every single DBTL cycle, but could, through multifidelity approaches, improve the quality of the active learning processes to design new strains. An alternative example of a hybrid lab, where humans and robots work together, can be seen in Dai et al. [36]. CRISPRi, clustered regularly interspaced short palindromic repeats interference. Created in BioRender. Garcia Martin, H. (2025) https://BioRender.com/b3×4qtc.

A variety of recent technological developments facilitate a hybrid-lab approach as well as fully automated scientific experimentation. These developments involve both software, for which widespread use of AI is enabling completely novel capabilities, and hardware, for which new automated experimental processes are becoming available at an accelerated pace, and potentially disruptive technologies are available.

Novel AI approaches for experimental design, protocol creation and checking, as well as troubleshooting of automated processes have recently emerged [9,19–23]. These AI tools hold the promise of freeing researchers from the need to generate low-level instructions for operating robotic equipment. This facilitates the use of automated processes by nonexperts and allows researchers to focus on high-level scientific questions [9]. However, failure rates and the required level of human oversight for these approaches in a production system remain unclear. Furthermore, auxiliary processes, which use a human-in-the-loop approach, would require upgrades in robotic control and data analysis strategies for these tools. The LLMs used for robotic control should be able to draft instructions for both robots and humans, making the avoidance of collisions and general safety a critical consideration. In terms of data analysis, new approaches such as multifidelity optimization [24,25] are needed, which combine robotic- and human-generated data and take into account their differences in quantity, quality, and type. Moreover, the integration of regulatory considerations (e.g. robust data traceability, good manufacturing practice compliance, or cybersecurity safeguards [26,27]) at this level might be advantageous.

In terms of hardware, automated solutions based on well-established liquid handling platforms have been recently proposed, including DNA library preparation [28], pH adjustment [29], DNA assembly [30], or strain construction [31]. Currently, processes such as plasmid transformation and colony picking are automated through commercial machines that mimic human behavior (e.g. an Echo Acoustic Liquid Handler, a Hamilton Vantage, a QPix 460 [32]). Alternative technological approaches show the potential to free science from the constraints imposed by mimicking human behavior [33], such as microfluidic droplet systems that reduce demands in space and reagents [34]. Finally, it is worth mentioning the advent of affordable humanoid robots [35], which could, in principle, substitute humans in diverse lab tasks.

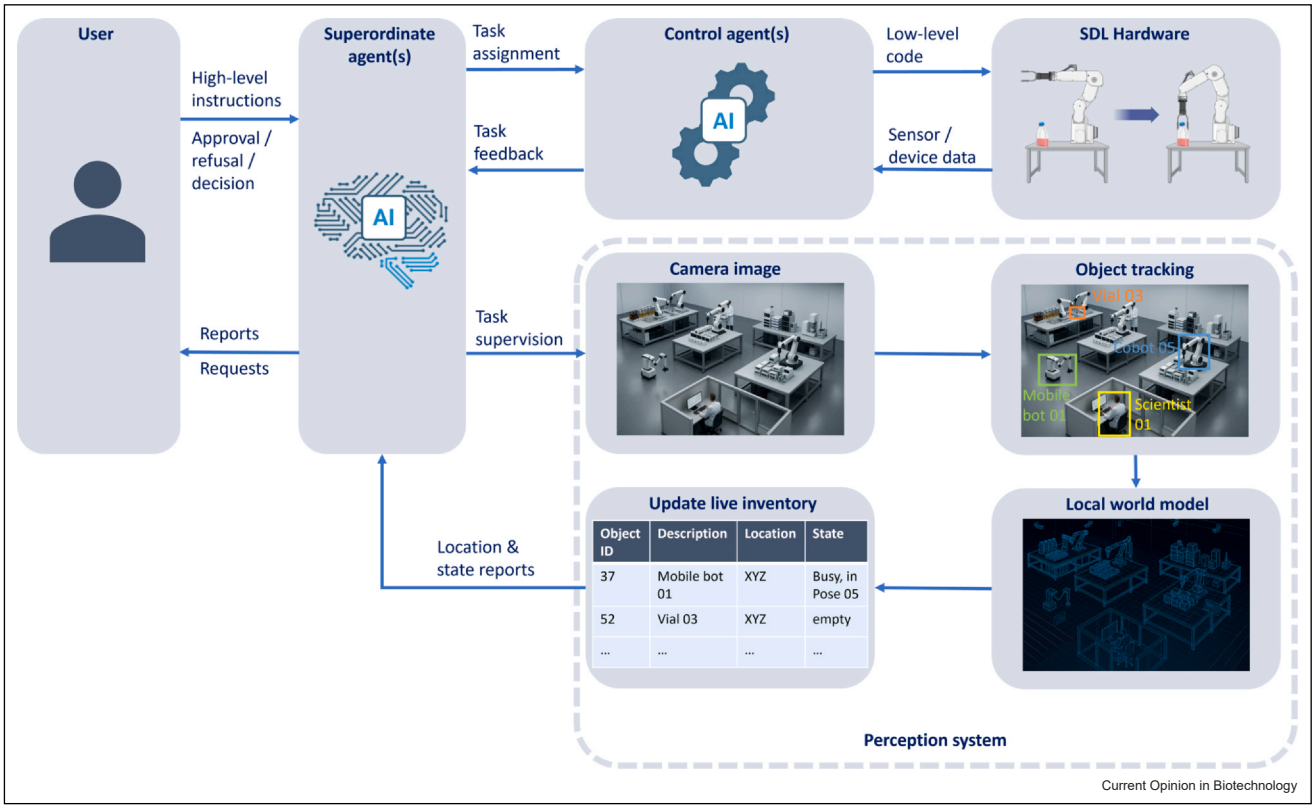
## Designing the future lab: human vs machine-centric laboratories

Designing laboratories around automation often gives rise to a false dichotomy: spaces need not be built either for people or for machines. Evidence from SDLs in chemistry and bioscience points to a pragmatic hybrid approach, as described above: automated execution in modular robotic work cells combined with human access points for oversight, anomaly triage, and sample entry [8,37–40]. Standardized unit operations, reconfigurable flow paths, and software-addressable hardware enable uninterrupted, high-throughput experimentation while preserving a human accountability layer [41].

A mid-term trajectory for ergonomics could be perception-driven autonomy. Rather than 'teaching' fixed positions for robotic devices and step-by-step procedures in an abstract computer language, SDLs will interpret natural language and maintain a space-resolved real-time model of the laboratory derived from multi-camera vision. From this local model of the laboratory, the orchestrator, which manages the workflows, continuously infers object locations, free paths, and safety envelopes [42]. In a biotech context, this perception layer could track liquid levels and turbidity during extractions or fermentations, read barcodes/labels to confirm identities and containment, and verify lid/door states before moves. The same local map supports live inventory of consumables, on-the-fly collision avoidance, and faster, safer error recovery. Crucially, it lifts programming to a meta-level: scientists or higher-level LLMs specify aims, and the orchestrator compiles these high-level tasks to scheduled low-level robot instructions. The outcome is not a strict machine-first design, but a genuinely hybrid environment whose devices and floor plan are co-optimized for robots and people (Figure 2). The perception-driven lab design would allow the controlling agent to supervise and instruct both robots for fully automated core processes and humans for partially automated or manual auxiliary process steps while getting real-time feedback for increased safety and faster error recovery.

Early precursors of cooperative chemical and biolabs using agentic AI already exist: *Coscientist* maps natural-language goals to lab application programming interfaces [9]; *ChemCrow* augments LLMs with domain tools [10]; and *AlphaEvolve* illustrates evaluator-in-the-loop improvement of code and controllers, an approach that can evolve bioprocess control stacks under human governance [43]. Computer vision has already been successfully employed for automating and supervising laboratory procedures such as liquid-level detection [44], titration [45], phase-behavior characterization [46], reaction monitoring [47–49], and even cell cultivation [50]. Multiple studies have investigated computer-vision-based object detection [51,52], robot control [53], and 3D-model generation [54] for life science laboratories. Further development and consolidation of these different aspects of agentic laboratory controllers, image analysis, and model generation are required to enable true perception-based autonomous control of complex multi-device SDLs. Recent advances independent of life sciences in world-model agents (*Genie*) and generalist control

**Figure 2**




Concept of perception-aware autonomous hybrid-labs. The user is in interaction with a superordinate agent for giving instructions and making decisions while receiving requests and status reports. The superordinate agent translates high-level user goals into tasks for control agents, which compile them into low-level robot code for SDL hardware; bidirectional links return device and sensor feedback. Concurrently, a perception module (dashed box) aggregates multicamera feeds, performs object detection/tracking, and maintains a spatial digital twin of the lab. This situational model keeps inventory current, maps safe motion corridors, and defines exclusion zones. With that context, the superordinate agent can orchestrate both people and robots, anticipate collisions, and recover from faults rapidly. Programming shifts from hand-coded coordinates to goal-level instructions, and the workspace is intentionally co-designed for shared use — modular cells deliver throughput while humans remain in the loop for oversight, non-automatable steps, exceptions, and handoffs.

(*DreamerV3*) strengthen this trajectory toward perception-grounded, instruction-level orchestration in labs [55–57].

User experience is shifting accordingly with the adoption of AI agents. Low-/no-code and natural-language interfaces reduce the barrier to automation while preserving expert intent, with canonical abstractions for unit operations, for example, by separating a process into high-level instructions such as 'dilute', 'grab', 'place', and 'measure absorbance' [9]. Dashboards should surface situational evidence (live process data, model uncertainty, and out-of-distribution alerts) so human operators can intervene decisively [8,38,40]. To keep the hybrid lab safe and accountable, especially in highly regulated environments such as biopharmaceutical production, guardrails must be built into the design: (i) clear decision tiers (i.e. when the system only suggests vs when it may act autonomously), (ii) enforced human checkpoints whenever measurements fall outside expected ranges, and (iii) auditable activity logs that explain what was measured, what the system proposed, and what was executed — written compatibly with regulatory requirements [8,38–40].

## Autonomous labs for bioprocess engineering: challenges from scale-up to manufacturing

While the promise of SDLs is most apparent at small experimental scales (ca. 1–250 mL), it is the transition to larger scales (ca. 50–200,000 L) that represents the most important challenge to realizing automation's full impact. At small scales (i.e. screening), high-throughput strain engineering and parallelized workflows dominate. However, the transition to pilot-scale and manufacturing environments is nontrivial because it is characterized by nonlinear process behavior, changing bioreactor dynamics, and differences in monitoring and control infrastructure [58].

To bridge this divide, digital twins have emerged as a powerful concept. By creating virtual representations of bioreactors and downstream operations, digital twins allow researchers to test process modifications *in silico* before implementation at scale [59,60]. In this context, uncertainty-aware modeling and process optimization are important to achieve reliable scale-up when acting with complex systems such as living catalysts. Frameworks such as Bayesian optimization, a data-driven, probabilistic approach, recently gained traction for bioprocess development and are frequently combined with lab automation to drive tasks from strain selection to process optimization [61–63]. When combined with multifidelity approaches — linking insights from bench-scale experiments with pilot-plant data — these models enable more reliable predictions of process performance across scales [25].

While multifidelity approaches have been applied in adjacent tasks such as reactor design or chemical discovery [64,65], applications in bioprocess engineering are scarce [25,61]. To successfully employ multiscale models for bioprocess development and benchmark algorithms across institutions, defining open 'scale-transfer benchmarks' would be transformational. Such standardized cases would compare strain and condition outcomes between laboratory and pilot settings in defined test cases, thus further supporting reproducibility and benchmarking.

Recent discussions also address the scale limits of SDL concepts in bioprocessing: while fully autonomous cycles excel at micro- to laboratory scale, their direct application diminishes as processes approach pilot and production volumes, where safety, regulatory oversight, and complex fluid dynamics may impose stricter boundaries. For large-scale operations, automation efforts are best implemented as hybrid systems, combining digital twins, advanced control, and human oversight rather than unrestricted autonomy [66]. In this context, human-in-the-loop optimization [67] is a promising direction to combine human expertise with automated and data-driven discovery. Recent advances in collaborative or preferential Bayesian optimization demonstrate how algorithmically derived proposals for experiments can be complemented by human preferences and knowledge [68,69].

## Gaps and demands to realize self-driving labs and autonomous discovery

AI and machine learning are becoming ubiquitous in our lives, both in the personal and the professional context. More recently, LLMs have created a surge in their visibility by tapping into the 'non-expert' user market through colloquial language (e.g. ChatGPT). SDLs should strive to do the same for the biotechnology community: open it to a larger audience and explore broader research possibilities. However, there are several gaps that need to be bridged to realize those futuristic laboratories where humans and robots work together seamlessly.

Language barriers present major obstacles when software developers, biologists, and automation engineers have to communicate across disciplinary jargon. LLM-based application programming interfaces can eliminate these field-specific complexities. However, safeguards must be constructed against hallucinations, security vulnerabilities, misrepresentations, and other limitations of LLMs before end-users can use vibe-coding (i.e. intuitively code new applications through conversations in natural language [70]). We expect that professional developers and scientists, however, will remain essential for debugging and validating the resulting data.

Cost, accessibility, and large footprints of SDLs can prevent widespread adaptation. Current financial struggles of the synthetic biology industry present a sobering economic reality [71]. Million-dollar biofoundries, without common standards for protocols, metadata, and data exchange, may create isolated silos of biased and incomplete datasets, which is squarely at odds with what AI models require for effective training. Recent community initiatives [59,72–74] illustrate how standardization and AI-assisted planning can elevate automation beyond the device layer. The Intent Parser and Open Protocol Interface Language translate human-authored objectives into structured instructions, enabling autonomous agents to assemble and execute experimental protocols consistently [73]. The protocol activity modeling language complements this by providing a formal representation for complex, branching workflows, supporting verification and reuse across laboratories [74]. Lessons from DARPA's SD2 program show that shared vocabularies and metadata services are crucial for orchestrating discovery across distributed SDL sites [75]. These examples demonstrate how rigorous data and metadata standardization and tracking can facilitate scientific discovery and address regulatory requirements. More broadly, the Bioprocessing 4.0 vision necessitates enterprise-scale architectures where digital twins, scheduling engines, and literature-mining agents cooperate to align experiments with higher-level research goals and regulatory expectations [59].

Finally, AI will not only support smart data utilization but also advance intelligent lab-automation hardware that drives future labs [29,76,77]. Condensing modern bio-research capabilities into modular, reusable setups will transform the enormous laboratory footprint into manageable 'assembly lines'. This will require miniaturizing some processes into chip-based microfluidic devices [78,79] and integrating other capabilities through conveyor belts or mobile robots. The focus must be set

on making each module independently verifiable and serviceable, which will render the whole platform easily re-configurable.

## Conclusions

AI and machine learning are quickly becoming essential pillars of automated experimentation. The vision of fully autonomous bioprocess development from strain engineering to manufacturing scale remains compelling; yet the current reality points toward a more nuanced trajectory. While SDLs have demonstrated remarkable success in chemistry and materials science, bioprocessing faces distinct challenges that, at least initially, point toward an era of hybrid labs. The primary bottleneck is no longer hardware maturity: liquid handlers, robotics, and analytical instruments have reached sophisticated levels. Instead, we are limited by the orchestration of complex, multiscale workflows under regulatory and safety constraints that demand human oversight.

The next three to five years are likely to see the emergence of modular hybrid systems where AI agents and LLM-based tools take on routine decision-making, protocol translation, and troubleshooting, while humans remain central for anomaly detection, strategic planning, and safety-critical judgment. This balance is not a compromise but a necessity, reflecting the unique challenges of scaling from high-throughput strain engineering to pilot plants and manufacturing. Alongside automation hardware, digital twins, multifidelity optimization, and standardized data frameworks provide promising scaffolds to bridge this gap. However, progress will most likely depend less on isolated breakthroughs than on coordinated community action.

Realizing SDLs for bioprocess engineering will therefore require universal standards for protocols and metadata, benchmarks for scale transfer, and sustainable economic models that extend automation beyond elite biofoundries. The next frontier is not the replacement of scientists but the careful design of hybrid systems, where human expertise and AI-driven automation complement one another to enable reliable, scalable, and responsible bioprocess innovation.

## CRediT authorship contribution statement

LMH conceptualized the manuscript and led its preparation. All authors contributed to the conceptual development, writing, and revision of the manuscript. SP, KG, MF, HGM provided domain-specific expertise, critical feedback, and editorial input. All authors read and approved the final version of the manuscript.

## Data Availability

No data were used for the research described in the article.

## Declaration of Competing Interest

HGM declares financial interests in XLSI bio.

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