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PERSPECTIVE ARTICLE

AI-enabled materials intelligence for lunar regolith: Design, fabrication, and lifecycle management

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Abstract

Artificial intelligence (AI) offers a new route to address the heterogeneity, data scarcity, and strongly coupled composition-process-structure-performance relationships of lunar regolith materials. This perspective reframes lunar regolith as a materials-intelligence problem that integrates materials data, physical knowledge, and AI-driven decision-making. Four pathways are examined: high-temperature densification, low-temperature consolidation, additive/composite manufacturing, and functionalized regolith materials. Priority AI interventions include physics-informed process modeling, composition-process-property learning, in-process monitoring, adaptive control, multi-objective design, and lifecycle prognostics for degradation and remaining-life prediction. We further propose an AI-enabled closed-loop framework linking resource characterization, material selection, autonomous fabrication, in-service monitoring, maintenance, and reuse. Future progress requires benchmark datasets, simulant-to-real transfer, uncertainty-aware learning, and closed-loop validation under lunar conditions. The central challenge is not merely to produce stronger regolith materials, but to establish trustworthy and deployable materials intelligence for long-term lunar infrastructure.

Keywords: Lunar regolith; Materials intelligence; AI-enabled materials design; *In situ* resource utilization; Physics-informed learning; Autonomous fabrication; Lifecycle management

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1. Introduction

In recent years, lunar exploration is gradually shifting from short-duration scientific missions to long-term surface presence and infrastructure deployment, and lunar regolith has also changed from general *in situ* resource candidate to key *in situ* material resource base supporting the construction, operation and maintenance of lunar surface.[1,2] Existing studies have been extensively explored around pathways such as sintering and melting, geopolymer consolidation, additive manufacturing, and lunar-regolith composites, and demonstrated their application potential in facilities such as landing sites, roads, shells, and protective layers.[3-5] Meanwhile, recent studies further indicate that lunar regolith-derived materials can not only undertake structural functions, but may also have thermal management, protection, and functional integration capabilities, suggesting a transition from traditional construction raw materials to multifunctional infrastructure materials.[6,7]

However, the development of lunar regolith materials still presents a materials-design problem that is fundamentally different from most terrestrial systems. Mineral composition, particle morphology, maturity, and particle-size distribution vary substantially across lunar regions, while only extremely limited quantities of authentic returned samples are available for laboratory investigation. Terrestrial simulants therefore remain indispensable, yet they cannot fully reproduce the composition and microstructural characteristics of real lunar regolith.[8,9] In addition, processing parameters such as sintering temperature, energy input, material formulation, deposition strategy, and curing conditions strongly influence pore evolution, interfacial integrity, mechanical properties, and thermal transport.[10] These relationships become further complicated under vacuum, severe thermal cycling, radiation exposure, and abrasive lunar dust. Consequently, lunar-regolith development is not merely a small-data optimization problem, but a coupled materials-design challenge involving simulant-to-real domain shift, extreme-environment extrapolation, and very limited opportunities for iterative in-situ experimentation.

Materials informatics, physics-informed learning, transfer learning, Bayesian optimization, multimodal learning, and autonomous experimentation have demonstrated considerable potential for accelerating materials characterization, property prediction, process optimization, and closed-loop discovery.[11,12] However, most existing materials-intelligence frameworks have been developed for terrestrial environments, where larger datasets, repeatable experiments, stable sensing systems, and continuous access to computational resources are often available. These assumptions are difficult to maintain for lunar-regolith applications because authentic samples are extremely scarce, simulant-to-real domain shifts are unavoidable, and models must operate under vacuum, severe thermal cycling, radiation exposure, and limited opportunities for *in situ* experimentation. Communication latency, constrained onboard computation, and possible sensor degradation further restrict frequent human intervention and model updating. Therefore, the key challenge is not simply to apply established AI tools to lunar materials, but to develop physics-informed, uncertainty-aware, transferable, and sufficiently autonomous materials-intelligence strategies specifically adapted to lunar conditions.

Recent evidence further broadens the functional potential of lunar regolith. For example, Chang'E-5 lunar agglutinates have demonstrated exceptionally low thermal conductivity under vacuum, indicating that regolith-derived materials may serve not only as structural feedstocks but also as thermal-management and multifunctional components.[7] This finding reinforces the need to move beyond the conventional objective of producing lunar analogues of terrestrial bricks or concrete. Instead, the key challenge is to determine how material composition, processing, structure, and service performance can be jointly designed under lunar-specific constraints. Accordingly, this Perspective examines four major regolith-derived material pathways and evaluates where AI can provide the greatest value in process modeling, property prediction, autonomous fabrication, and lifecycle decision-making. Emphasis is placed on simulant-to-real transfer, uncertainty-aware prediction, and closed-loop validation, with the aim of defining a materials-intelligence framework that is reliable and deployable under lunar conditions.

2. Lunar regolith as an AI-enabled materials design problem

Lunar regolith should be regarded as an AI-enabled materials-design problem governed jointly by feedstock characteristics, processing conditions, material evolution, and service environments. Although sintering, laser or microwave melting, geopolymer consolidation, and additive manufacturing have demonstrated the feasibility of *in situ* regolith processing, material performance cannot be determined by the processing route alone. Variations in mineral composition, particle-size distribution, morphology, and maturity can influence energy absorption, melting or reaction behavior, densification, pore evolution, and interfacial integrity, which in turn govern mechanical and thermal properties. These coupled relationships become further complicated by process fluctuations and exposure to vacuum, thermal cycling, radiation, and abrasive lunar dust. Consequently, the central materials challenge is to establish reliable composition-process-structure-property relationships across heterogeneous regolith feedstocks and lunar service conditions.

As shown in Figure 1, lunar-specific environmental and operational constraints impose distinct requirements on materials design. Vacuum and extreme thermal cycling affect heat transfer and damage evolution, while feedstock variability and the scarcity of authentic samples complicate process-structure-property mapping. Abrasive dust, radiation, limited onboard sensing and computation, communication latency, and restricted opportunities for *in situ* trial-and-error further increase the need for autonomous fabrication and reliable lifecycle assessment. Lunar-regolith materials design is therefore a multi-objective and strongly physics-constrained problem.

A particularly important challenge is the transfer of knowledge from terrestrial regolith simulants to

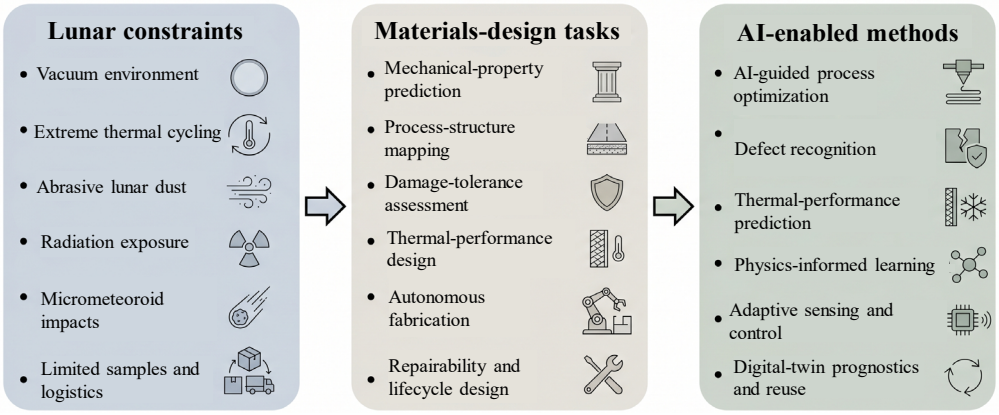


Figure 1. From lunar environmental constraints to AI-enabled materials design for intelligent lunar infrastructure

authentic lunar materials. Simulants enable relatively large experimental datasets, but differences in mineralogy, particle morphology, maturity, and agglutinate content may introduce systematic domain shifts when models are applied to returned or site-specific lunar regolith. A practical strategy is to combine multi-fidelity learning with transfer learning, using abundant simulant and numerical data for initial model development and limited returned-sample measurements for few-shot calibration. Active learning can further prioritize experiments with the highest expected information gain, thereby reducing the consumption of scarce lunar samples. Because extrapolation beyond the calibrated domain is unavoidable, uncertainty quantification and out-of-distribution detection should accompany predictions to identify cases requiring additional characterization or ground confirmation.

AI should therefore act as a decision-support layer linking material characterization, process modeling, fabrication, and performance assessment. Multimodal learning can integrate spectral, imaging, and mineralogical data for feedstock grading; physics-informed learning can improve prediction under limited-data conditions; surrogate models and Bayesian optimization can reduce costly formulation and process experiments; and visual and thermal sensing can support defect recognition and adaptive control. However, these methods remain constrained by domain shift, model extrapolation, sensor reliability, and onboard computational resources. The key challenge is therefore to identify AI approaches that remain physically credible, uncertainty-aware, and operationally feasible under lunar conditions.

3. Regolith material pathways and AI intervention points

Lunar regolith materials research is shifting from verifying constructability to material design for smart infrastructure. As shown in Figure 2, four main pathways correspond to different AI intervention focuses, including process optimization, performance prediction, process monitoring, adaptive control, and lifecycle assessment. Table 1 further compares their engineering forms, key limitations, and priority AI tasks.

3.1. High-temperature densification: Process modeling and optimization

High-temperature densification mainly includes sintering, melting and related thermal processing, which can consolidate lunar regolith with little or no imported binder for applications such as landing pads, pavements, and protective components.[13] Recent microwave-sintering experiments on lunar highland regolith simulants, for example, achieved a compressive strength of 142.12 MPa at 995 °C, demonstrating the strong dependence of material performance on composition and thermal-processing conditions. The key is not only to maximize strength, but also to control the relationships among energy input, temperature field, densification, pore evolution, and defect formation. Physics-informed surrogate models and Bayesian optimization can help predict thermal responses, identify stable process windows, and reduce the experimental and energy costs associated with process optimization.

3.2. Low-Temperature Consolidation: Composition–process–property learning

Low-temperature consolidation mainly includes geopolymerization, sulfur-based binding and other low-temperature forming routes, and is suitable for blocks, shell units and local repair materials.[14] Compared with high-temperature densification, these approaches

Table 1. Regolith-derived material pathways, data availability, engineering constraints, and priority AI interventions

Material pathway	Representative engineering forms	Data availability / validation status	Main challenge	Priority AI intervention
High-temperature densification	Landing pads, pavements, protective shells	Moderate simulant-based data; limited validation using authentic lunar samples	High energy demand, non-uniform thermal fields, and scale-up uncertainty	Physics-informed process modeling, Bayesian optimization, and defect prediction
Low-temperature consolidation	Blocks, shell units, repair materials	Primarily simulant-based experimental data; limited authentic-sample and long-term durability validation	Feedstock variability and uncertain durability under lunar conditions	Composition–process–property learning, mixture optimization, and uncertainty quantification
Additive and composite manufacturing	Printed components, lightweight modules, interface parts	Growing terrestrial and simulant process data; limited validation under lunar environmental conditions	Interlayer defects, anisotropy, and process instability	In-process monitoring, anomaly detection, and adaptive control
Functionalized regolith materials	Insulation layers, multifunctional panels, sensor-compatible units	Sparse and early-stage data; very limited lifecycle validation	Low technology maturity, multi-objective trade-offs, and limited lifecycle data	Multi-objective inverse design, performance prediction, and lifecycle prognostics

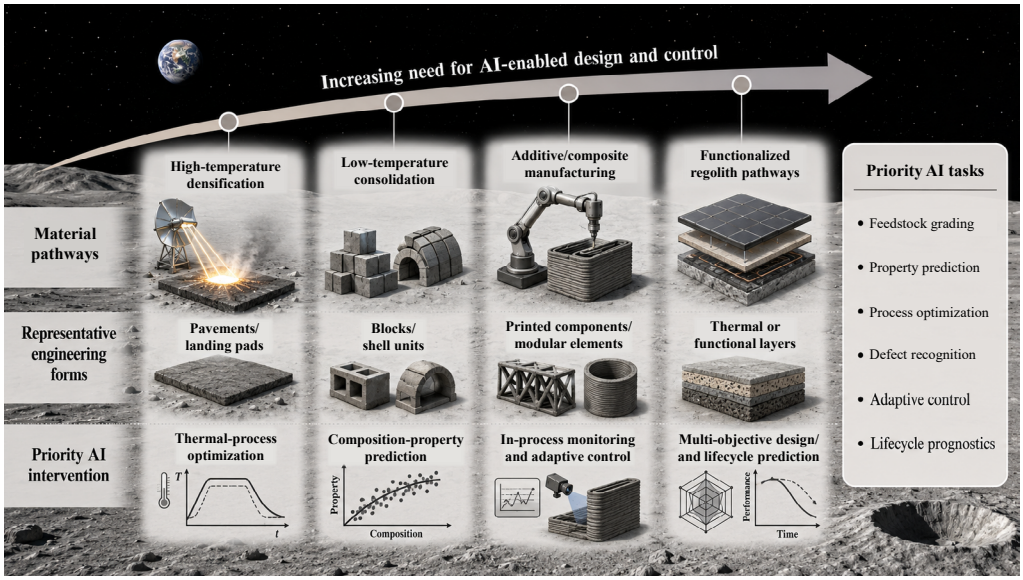


Figure 2. Regolith material pathways and priority AI intervention points for intelligent lunar infrastructure

generally require lower processing temperatures and provide greater flexibility for modular fabrication and *in situ* deployment. For example, a lunar-regolith-simulant geopolymer achieved a 7-day compressive strength of 58.8 MPa after curing at 60 °C, illustrating the strong influence of processing conditions on material performance. Its properties are also sensitive to regolith composition, particle grading, activator ratio, curing conditions, and subsequent thermal exposure. Composition–process–property learning, surrogate models, and uncertainty quantification can therefore support formulation screening and property prediction under limited experimental data while accounting for variability among regolith feedstocks and service conditions.

3.3. Additive and composite manufacturing: Monitoring and adaptive control

Additive and composite manufacturing extends lunar-regolith processing from material formation to component-scale fabrication, enabling *in situ* production of lightweight

modules, interface parts, and other customized elements.[15] However, weak interlayer bonding, pore anisotropy, residual stress, and process fluctuations can reduce structural reliability. AI-assisted process models can relate thermal history, deposition parameters, and toolpaths to defect formation, residual stress, and microstructural evolution. In parallel, visual, thermal, geometric, and equipment-state data can support in-process defect detection and quality assessment. Coupling these predictions with surrogate models and adaptive control can further optimize energy input and toolpaths, thereby improving the stability and repeatability of autonomous lunar manufacturing.

3.4. Functionalized regolith materials: Multi-objective design and lifecycle intelligence

Functionalized lunar regolith materials represent an evolution from single structural functions toward thermal insulation, protection, sensing compatibility and multifunctional integration.[16] Recent measurements of Chang'E-5 lunar agglutinates have demonstrated exceptionally low thermal conductivity under vacuum, highlighting the potential of regolith-derived materials for functions beyond structural load bearing. Their design, however, requires simultaneous consideration of mechanical performance, thermal management, manufacturability, energy consumption, durability, and recyclability. Multi-objective machine learning and inverse design can help identify trade-offs among these competing requirements and screen material composition and structural configurations for specific infrastructure functions. Combined with digital-twin based degradation prediction, these approaches may further support long-term performance assessment under thermal cycling, radiation and impact, providing a basis for maintenance and reuse.

Overall, the four regolith-material paths are complementary rather than mutually exclusive and require different AI interventions: high-temperature densification emphasizes thermal-process optimization, low-temperature consolidation focuses on composition-process-property learning, additive manufacturing relies on in-process monitoring and adaptive control, and functionalized materials require multi-objective design and lifecycle prognostics.

4. AI-enabled closed-loop materials intelligence for lunar infrastructure

The key to long-term lunar infrastructure lies not only in fabrication, but also in establishing a continuous closed loop from resource characterization and material design to fabrication, in-service monitoring, maintenance, and reuse. As shown in Figure 3, AI serves as a materials-intelligence layer connecting these stages through perception, prediction, optimization, and control. The information exchanged across the loop includes feedstock descriptors, formulation and process windows, as-built quality and defect data, degradation indicators, remaining-life estimates, and associated uncertainty. These data are progressively fed forward to support fabrication and performance prediction and fed back to update material selection, process parameters, and maintenance strategies. In this way, regolith-derived materials can evolve from static construction products into lifecycle-managed infrastructure materials that adapt to changing mission requirements and service conditions.

4.1. From regolith sensing to data-driven material selection

Lunar regolith varies substantially across surface regions in particle size, mineral composition, morphology, and maturity. Material design should therefore begin with resource characterization and feedstock grading. AI can integrate remote sensing spectra, particle images, *in situ* measurements, and terrain data to identify usable regolith and evaluate its processing suitability.[17,18] The resulting feedstock descriptors, including mineralogical composition, particle-size distribution, morphology, and associated uncertainty, can then serve as standardized inputs for pathway selection, formulation optimization, and property prediction. This enables lunar-regolith development to shift from empirical trial-and-error toward data-driven material selection tailored to mission requirements.

4.2. From autonomous fabrication to adaptive process control

High-temperature densification, low-temperature consolidation and additive manufacturing all rely on robotic execution and real-time process control. AI can integrate visual, thermal, geometric, and equipment-state data to identify temperature non-uniformity, interlayer defects, and geometric deviations, while surrogate models and model predictive control can dynamically adjust energy input, deposition rate, and toolpaths. Fast process-level updates can support autonomous corrections within validated operating windows, whereas slower model updates can incorporate accumulated defect and performance data for model recalibration. Routine parameter adjustments may be performed onboard, while major formulation changes, out-of-distribution conditions, or safety-critical decisions should require ground confirmation. This hierarchical control strategy enables a practical perception-prediction-optimization-control loop

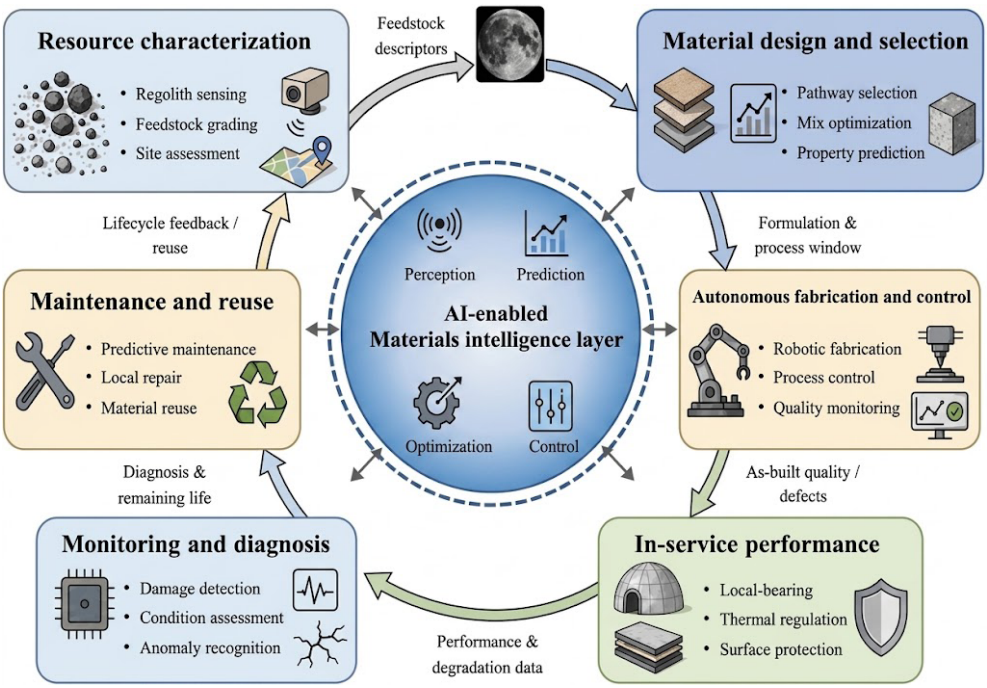


Figure 3. AI-enabled closed-loop materials intelligence framework for regolith-derived lunar infrastructure

while maintaining reliability under communication and computational constraints.

4.3. From in-service monitoring to lifecycle prognostics and reuse

Long-term lunar missions require infrastructure to shift from passive inspection toward condition awareness and predictive maintenance. Crack propagation, thermal instability and functional degradation may occur in pavements, shells, protective layers, and thermal-control components under thermal cycling, lunar-dust erosion, and local impacts. AI can integrate strain, temperature, imaging, and operational data for anomaly detection, condition assessment, and remaining-life prediction. Digital twins can further link manufacturing history, environmental loads, and service responses to support local repair, component replacement, and material reuse. Degradation indicators, defect-growth statistics, remaining-life estimates, repair records, and associated uncertainty should be fed back to material-design and process-optimization stages to update formulations, process windows, and maintenance thresholds. Deployment of this closed-loop framework should proceed from terrestrial lunar-environment simulation to small-scale lunar demonstrations and, ultimately, infrastructure-scale implementation.

5. Future directions

Despite its potential, AI-enabled materials intelligence for lunar regolith faces important limitations. Models trained primarily on simulants may fail when extrapolated to authentic or site-specific lunar materials, particularly under extreme data scarcity and environmental conditions outside the training domain. Black-box predictions also raise certification and trust concerns for safety-critical infrastructure, while abrasive dust, radiation, and thermal cycling may degrade sensors and introduce drift into the monitoring loop. In addition, limited onboard computation, energy, and communication capacity constrain the complexity and update frequency of deployable AI models. These limitations require uncertainty-aware prediction, out-of-distribution detection, robust sensing, and clearly defined boundaries between autonomous and ground-confirmed decisions.

Future research should therefore prioritize open benchmark datasets linking regolith composition, particle characteristics, processing parameters, microstructure, and multifunctional performance. Multi-fidelity and transfer learning should be further developed to bridge simulants and scarce returned samples, while physics-informed models and uncertainty quantification can improve reliability under limited-data conditions. Finally,

AI models should be progressively validated through lunar-environment simulation, autonomous fabrication experiments, in-service monitoring, and staged lunar demonstrations. The long-term goal is not simply to improve individual material properties, but to establish a trustworthy, interpretable, and deployable materials-intelligence platform for lunar infrastructure.

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Conflict of interest

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Author contributions

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Ethics approval and consent to participate

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Consent for publication

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Availability of data

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