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Environment–process–structure–property linkages in additive manufacturing

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Environmental conditions fundamentally shape the reliability and sustainability of additive manufacturing. As additive manufacturing moves into real-world environments, these factors need to be considered in modelling and design.

Additive manufacturing reduces material waste, enables lightweight design and supports decentralized production, compared with conventional processes[1]. Environmental variables such as temperature, humidity, vibration, gravity and pressure, and other factors such as airflow, illumination or particulate contamination, can strongly influence the microstructure and mechanical performance of printed parts[2,3]. As additive manufacturing moves beyond laboratory settings into industrial and field-scale applications, the ability to understand and respond to these conditions becomes essential. In this Comment, we emphasize the importance of incorporating environmental conditions into additive manufacturing research and application, considering what we refer to as environment–process–structure–property (EPSP) relationships.

EPSP relationships treat environmental conditions as active drivers that shape the relationships between printing process and printed structure, not as external background settings. Temperature fluctuations, humidity changes, mechanical vibrations and gravitational orientation can all interact with processing conditions during fabrication and affect outcomes (schematic shown in Fig. 1). For instance, elevated ambient temperatures can reduce cooling rates and disrupt thermal gradients[4], which would impact printing on a hot day. These changes could result in internal warping, the build-up of residual stress and weaker bonding between layers. By contrast, cold environments can cause incomplete fusion and brittle interfaces due to rapid solidification[5].

Humid environments introduce additional challenges. Moisture absorbed by polymers and resins reduces interlayer adhesion[6]. As printing progresses, absorbed water can vaporize, leaving behind pores or trapped bubbles within the material. High humidity can also accelerate surface oxidation, which degrades melt quality and reduces long-term durability of metal and ceramic systems, as well as modulating hydration kinetics in 3D printed concrete, thereby shaping microstructural evolution and influencing long-term performance[7]. Vibration is another often-overlooked environmental factor that can originate from sources such as traffic or nearby construction[8]. In the laboratory, equipment such as vacuum pumps, centrifuges and cooling systems can generate local vibrations, which can shift deposition paths, cause layer misalignment, increase surface roughness and introduce microcracks that weaken the printed part. Moreover, gravity and part orientation dictate how material flows and settles. Unsupported regions could sag or deform if improperly aligned, leading to geometric distortion and anisotropic performance[9].

Despite the impact of environmental conditions on microstructure and performance, they are rarely integrated into additive manufacturing design frameworks at present. Instead, process–structure–property (PSP) relationships have been the foundation for understanding material behaviour in additive manufacturing. PSP emphasizes the control of processing parameters such as print speed, flow rate, energy input and cooling rate to tailor microstructure and performance[10]. Experimentally, maintaining stable ambient temperature and humidity levels requires specialized enclosures with thermal regulation and humidity control, which increase system complexity and calibration demands; most commercial printers do not have these capabilities. On the modelling side, incorporating environmental variability demands coupling thermal transport, phase change and moisture diffusion with toolpath-dependent deposition kinetics. These simulations rely on computationally intensive multiphysics solvers and real-time boundary tracking, which align poorly with slicer-based workflows. As a result, digital twins often do not include environmental effects, limiting their applicability in real-world or uncontrolled settings[11].

Artificial intelligence (AI) could help to interpret environment–process interactions and enable adaptive control during printing[12]. While conventional systems lack effective coordination across sensors, AI can overcome this by integrating data from multiple sensors to capture how fluctuations in temperature, humidity, vibration and gravity affect thermal distribution, material flow and interfacial behaviour[13]. Use of AI tools could also potentially provide predictive control by linking environmental and process states with structural evolution[14]. Through reinforcement learning or AI-driven digital twins, systems can anticipate defects and adjust toolpaths, energy input or timing in real time to ensure print quality under variable conditions[15].

These capabilities are especially valuable in settings where environmental control is limited, such as space, disaster zones, remote communities and defence operations. In these contexts, adaptive additive manufacturing enables on-demand production of mission-critical components. Examples include fabricating water purification parts for off-grid areas, medical tools for emergency response and structural elements for rapid shelter construction. This approach reduces reliance on complex supply chains and supports production continuity in extreme environments.

The next phase of additive manufacturing should be grounded in an EPSP perspective that treats environmental conditions as integral components of process design, providing the foundation for scalable and resilient additive manufacturing.

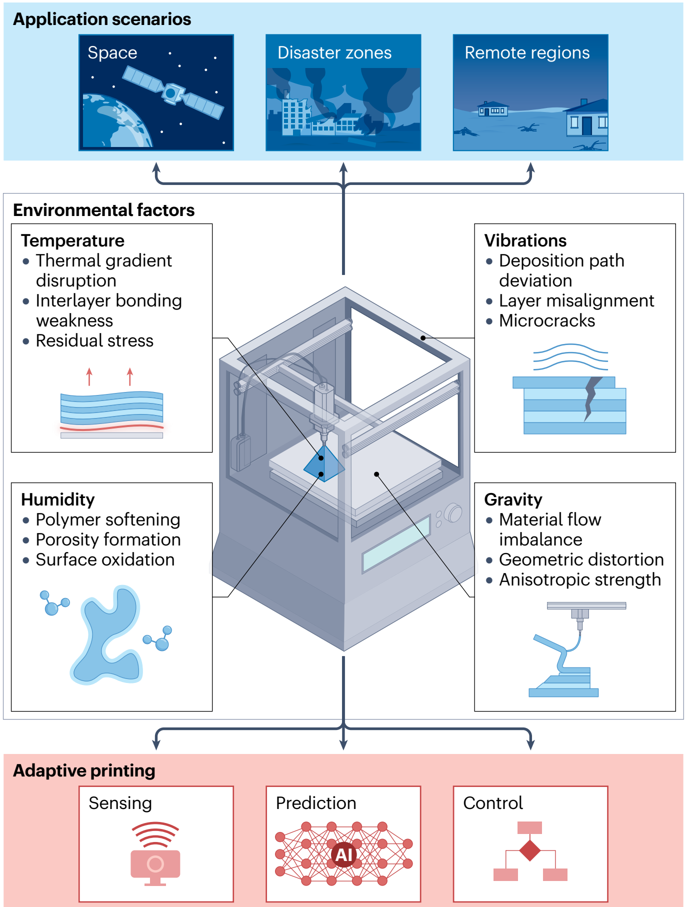

Fig. 1 | Environmental impacts and AI-enabled adaptation in additive manufacturing. Environmental factors such as temperature, humidity, vibration and gravity affect printed part quality through mechanisms including thermal stress, layer misalignment, porosity formation and anisotropic deformation. Artificial intelligence (AI)-enabled adaptive manufacturing combines real-time sensing, environmental prediction and autonomous control to compensate for these fluctuations, enabling reliable production in uncontrolled settings such as space, disaster zones and remote field sites.

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Competing interests

The authors declare no competing interests.