

Causal Inference in Photopolymer Process Development: Interventions, Confounding, Transportability and Mechanistic Claims

Separating association, prediction and cause in coupled material-process systems

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Abstract

Photopolymer process datasets frequently contain strong correlations among formulation, machine, exposure, geometry and final properties. Correlation can support prediction but does not by itself establish a causal mechanism. This review translates causal-inference concepts into photopolymer process development. It distinguishes interventions from observations, identifies common confounders and mediators, and explains why feature importance, regression coefficients and predictive accuracy cannot automatically be interpreted as causal effects. A process-structure-property graph is proposed for formulation, optical dose, thermal history, conversion, network state, geometry and measured performance. The framework requires causal assumptions to be explicit, tests transportability when moving between printers or material states, and treats mechanistic claims as stronger than predictive claims. Published materials and additive-manufacturing work demonstrates growing use of causal and physics-guided analytics, but photopolymer-specific causal identification remains an evidence gap requiring designed interventions.

Keywords: causal inference · photopolymer process development · directed acyclic graph · confounding · intervention · transportability · process-structure-property

1. Why prediction is not causation

A model can predict dimensional error from exposure dose without proving that dose is the only or direct cause. Dose may covary with layer thickness, temperature, resin age or operator-selected process regimes. Likewise, a formulation component can appear strongly associated with modulus because it was tested only within a specific post-cure protocol. Predictive success therefore answers a different question from causal attribution. Causal inference begins by defining the intervention of interest: for example, what would change if irradiance were altered while relevant upstream conditions were controlled? This counterfactual question is not answered by feature importance alone.

2. A causal graph for photopolymer processing

A useful graph separates formulation identity and composition from process inputs, latent cure state and observed outputs. Optical absorption and scattering mediate how incident light becomes local absorbed energy; initiation, inhibition and mobility affect conversion; conversion and network formation affect shrinkage, modulus and solvent response (see ER-035, ER-031, ER-351 and ER-352); geometry and thermal history can modify each path. Measurements can also be nodes rather than truth. For example, a fitted working-curve parameter is derived from a measurement protocol and can carry protocol-specific bias. Treating it as a causal primitive may collapse several mechanisms into one number.

3. Confounding and selection bias

Confounding occurs when a variable affects both the exposure of interest and the outcome. In retrospective printer logs, operators may increase dose for difficult geometries or high-viscosity resins. A simple association between higher dose and failure may then reflect intervention in response to difficulty rather than harm caused by dose. Selection bias can arise when only successful prints reach mechanical testing. The dataset then conditions on survival, which may be influenced by both formulation and process. Causal conclusions from the surviving subset can therefore be distorted.

Table 1. Claim levels in process analytics

Claim level	Supported by	Insufficient evidence
Association	observed covariance	causal language
Prediction	validated out-of-sample prediction	mechanistic attribution

4. Mediators and total versus direct effects

Conversion can mediate the effect of dose on modulus; temperature can mediate both reaction rate and viscosity; washing can mediate the effect of network state on extractables. Whether a mediator should be adjusted for depends on the causal estimand. Controlling for a mediator when estimating a total effect can remove part of the effect one intends to measure. This distinction is essential in photopolymer engineering because process chains are sequential. A direct effect of formulation on final modulus and a total effect through cure conversion answer different design questions.

5. Interventions and designed experiments

Randomised or deliberately blocked experiments provide stronger causal leverage than observational logs. A useful intervention changes one factor or a designed set of factors while balancing known confounders. Fractional factorial or response-surface designs remain valuable because they make the intervention structure explicit. Adaptive experimentation can also support causal questions, but selection

probabilities and stopping rules must be retained. Otherwise, adaptive sampling can create a dataset whose distribution is difficult to interpret retrospectively. Adaptive experimental design under explicit feasibility constraints provides a relevant adjacent manufacturing precedent [3].

6. Physics as a constraint on causal structure

Physics-guided process-structure-property frameworks in additive manufacturing show how domain knowledge can organise data and model relationships [2]. For photopolymer systems, reaction sequence, mass conservation, energy balance and optical transport can exclude impossible graph directions and motivate mediator structure. Physics does not eliminate uncertainty in causal assumptions. A known mechanism at molecular scale may not determine the dominant path in a printed geometry. The graph should distinguish accepted physical constraints from hypotheses to be tested.

Claim level	Supported by	Insufficient evidence
Causal effect	identified intervention or defensible adjustment	feature importance alone
Mechanistic effect	causal evidence plus physical/chemical corroboration	statistical direction alone

Table 2. Common confounding paths

Question	Potential confounder	Control strategy
dose -> dimensional error	geometry difficulty; resin age	randomise/block; record age
temperature -> conversion	viscosity; exposure timing	controlled thermal history
formulation -> modulus	post-cure protocol; specimen geometry	locked post-cure and geometry
wash -> extractables	network conversion; solvent age	measure conversion and solvent state

7. Transportability across machines and material states

A causal effect estimated on one printer is not automatically transportable to another if spectrum, irradiance field, separation mechanics or thermal environment changes. Transport requires identifying which causal mechanisms are invariant and which nodes have changed distribution or mechanism. The same issue applies across resin batches and post-cure workflows. A causal claim should specify the source population, target population and assumptions used to transfer the effect.

8. Mechanistic claims and evidence levels

A hierarchy is useful: association, predictive relationship, intervention-supported effect, and mechanistically corroborated effect. The final level requires consistency with physical or chemical evidence, not merely statistical identification. Materials-science work using causal discovery illustrates the value of explicit directed structures while also showing dependence on domain constraints [1]. Photopolymer papers should avoid language such as “controls”, “drives” or “causes” when the study design only supports association. Precise claim language is part of scientific quality.

9. Minimum reporting record

Causal analyses should report the causal question, graph or structural assumptions, exposure, outcome, adjustment set, intervention or observational design, missing-data handling, selection criteria, sensitivity analyses and transport assumptions. If causal discovery algorithms are used, constraints imposed by domain knowledge must be explicit. For photopolymer experiments, the state record should include formulation, spectrum, dose/irradiance, geometry, temperature, wash/post-cure and measurement method because these variables commonly sit on causal or confounding paths.

10. Qualification decision boundary

Causal inference can improve photopolymer process development by preventing predictive correlations from being promoted into mechanisms without adequate design. The principal engineering value is not a more sophisticated regression; it is a transparent statement of what intervention is being estimated, under which assumptions, and whether that effect is expected to transport to the target process. Direct photopolymer-specific causal-inference evidence remains limited. That gap should motivate controlled interventions rather than be filled by mechanistic inference from unrelated manufacturing systems.

11. Negative controls and falsification

Causal claims become stronger when the study includes perturbations that should not change the proposed mechanism. If a model asserts that a spectral-dose variable acts through conversion, then a negative-control endpoint unrelated to conversion can help reveal broad run-order or temperature effects. Likewise, intentionally blocking a suspected confounder can test whether an observed relationship persists when that path is closed. Falsification should be planned rather than added after a preferred graph is found. Competing directed acyclic graphs can imply different conditional independences or different responses to intervention. Experiments chosen to distinguish those predictions are more informative than simply collecting more observations under the same passive process.

12. Time ordering and feedback in manufacturing

Photopolymer workflows are temporally ordered, but feedback can complicate a simple acyclic representation. Operators may inspect early layers and alter process settings; adaptive machines may change exposure in response to sensed state; post-cure conditions may be selected based on print quality. The causal analysis must represent those policies or restrict the estimand to a fixed-policy regime. Time-dependent confounding also arises when prior exposure changes both current material state and future process choice. Longitudinal causal methods may be needed when repeated interventions occur, and a static regression on final summary variables can be misleading.

13. Measurement error in causal variables

Causal inference commonly assumes that variables in the graph are measured adequately. Photopolymer process variables often violate that assumption: nominal irradiance may differ from part-plane irradiance; fitted conversion proxies may be noisy; actual part temperature

may differ from chamber temperature. Measurement error can attenuate, reverse or otherwise distort estimated effects. The measurement model should therefore be integrated with the causal model where the error is consequential. Replicate or reference measurements can identify some error structures, while latent-variable approaches may be required for unobserved states. Claims should be weakened when the relevant causal variable is only indirectly measured.

14. Evidence gaps and research priorities

Direct interventional causal studies in photopolymer additive manufacturing remain uncommon relative to predictive modelling. A high-value research programme would publish pre-specified causal graphs for dose, temperature, oxygen, conversion, shrinkage and mechanical state, then test them with controlled interventions across at least two machines or spectra. Transportability deserves separate experiments rather than retrospective discussion. The same intervention should be repeated under a target-domain change with measured mediator states so that failure of transfer can be located in the causal chain.

References

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Competing interests

The author is Founder, CEO and CTO of 3Dresyns by Resyner Technologies S.L.; ER-403 contains no comparative recommendation between commercial products.

Data availability

ER-403 is a literature-based engineering review; no new experimental dataset was generated.