



Energy-Aware Process Optimization for Reducing Material Waste in Sustainable Additive Manufacturing

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Abstract

This study has examined energy-aware process optimization as a means of reducing material waste in sustainable additive manufacturing, with particular attention to metal powder-bed fusion and directed-energy-deposition processes in selected United States industrial and research settings. The central problem has been that additive manufacturing, although frequently characterized as near-net-shape and material-efficient, in practice incurs substantial material waste through support structures, un-fused and degraded powder, failed and out-of-specification builds, and post-processing removal, while simultaneously consuming high specific energy per unit of deposited material, so that gains in one objective are often obtained at the expense of the other. The purpose of the study has been to evaluate whether process parameter control and optimization, energy monitoring and specific energy efficiency, material flow modeling and waste reduction, thermal and melt-pool digital-twin fidelity, and data governance, standardization and compute jointly and significantly improve sustainable manufacturing and waste-reduction outcomes when energy consumption and material waste are treated as coupled objectives within a single multi-objective optimization framework rather than optimized in isolation. A quantitative, cross-sectional, case-based research design has been used, and data have been collected from additive manufacturing process engineers, materials and metallurgy specialists, sustainability and life-cycle-assessment analysts, machine and automation engineers, and manufacturing data scientists engaged in process development and production. Out of 281 distributed questionnaires, 241 valid responses have been retained, producing an 85.8% valid response rate. The analysis plan has included descriptive statistics, Cronbach's alpha reliability testing, Pearson correlation analysis, multiple regression modeling, hypothesis testing, a prototype multi-objective process-parameter optimization evaluation, and Python-driven analytical workflow validation. The findings have shown strong agreement across the constructs, with process parameter control and optimization recording the highest mean score of 4.25, followed by energy monitoring and specific energy efficiency at 4.18, material flow modeling and waste reduction at 4.09, sustainable manufacturing and waste-reduction outcomes at 4.03, thermal and melt-pool digital-twin fidelity at 3.97, and data governance, standardization and compute at 3.90. Reliability has been confirmed through Cronbach's alpha values ranging from .82 to .91, with overall reliability of .93. Correlation results have shown significant positive relationships between waste-reduction outcomes and process parameter control ($r = .69$), energy monitoring and efficiency ($r = .68$), material flow modeling ($r = .65$), thermal digital-twin fidelity ($r = .61$), and data governance ($r = .58$), all at $p < .001$. The regression model has been significant, $F(5, 235) = 55.63$, $p < .001$, explaining 54.2% of the variance.

Keywords

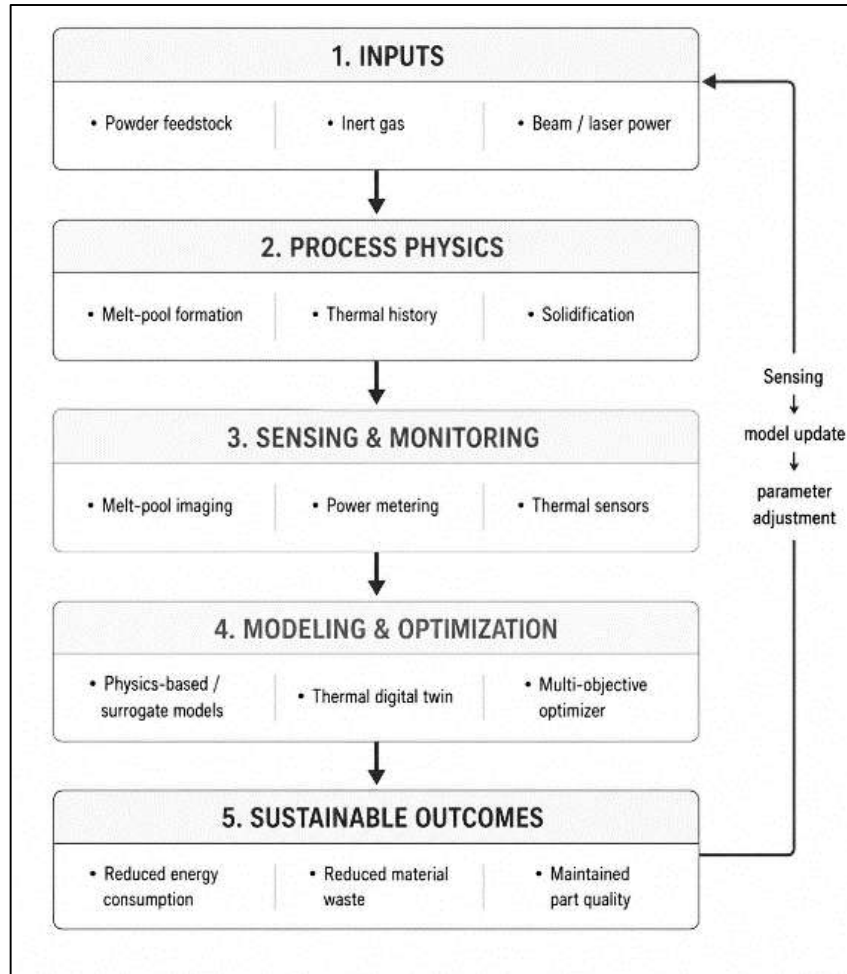
Additive Manufacturing; Sustainable Manufacturing; Energy-Aware Optimization; Material Waste Reduction; Multi-Objective Process Optimization; Melt-Pool Digital Twin.

INTRODUCTION

Additive manufacturing refers to the family of processes in which components are fabricated by the successive addition of material, typically layer by layer, from a digital model, in contrast to subtractive processes that remove material from a billet and to formative processes that shape it under constraint (Gibson et al., 2021). In metal additive manufacturing, the two dominant process classes are powder-bed fusion, in which a laser or electron beam selectively melts regions of a thin powder layer, and directed energy deposition, in which material is fed into a moving melt pool created by a focused energy source (DebRoy et al., 2018). Sustainable additive manufacturing, as used in this study, refers to the pursuit of these processes in a manner that minimizes the environmental burden per unit of functional output, with material waste and energy consumption as the two principal and frequently competing burdens. Material waste, in this context, denotes the fraction of input material that does not become part of the qualified final part, including sacrificial support structures, un-fused and thermally degraded powder that cannot be reused, failed and out-of-tolerance builds, and material removed in post-processing. Energy consumption is quantified through the specific energy consumption, the electrical or beam energy expended per unit mass of material consolidated, a metric that has been shown to be high for metal additive processes relative to conventional manufacturing and to vary strongly with process parameters (Baumers et al., 2016). The object of this study is the joint, energy-aware optimization of process parameters so as to reduce material waste and energy consumption together, treating them as coupled objectives rather than optimizing quality or throughput in isolation. Additive manufacturing is frequently described as near-net-shape and therefore material-efficient, and in favorable geometries it can achieve a buy-to-fly ratio, the ratio of input material mass to final part mass, far below that of machining from solid (Ford & Despeisse, 2016). This characterization, however, obscures substantial sources of waste that arise in practice. Support structures required to anchor overhangs and conduct heat can constitute a large fraction of deposited mass and are removed and discarded. Powder that is exposed to the process but not fused is recovered and, in principle, reused, but repeated thermal cycling degrades powder chemistry and morphology, so that a fraction must be discarded to maintain part quality (Abdur & Iftekhhar, 2021; Hossan, 2021). Build failures, whether from thermal distortion, porosity, or process instability, waste the entire deposited mass together with the energy expended to produce it. Life-cycle assessments of metal additive manufacturing have shown that when these sources are accounted for, the environmental advantage over conventional manufacturing is conditional rather than automatic, and depends strongly on process parameter selection, build orientation, support strategy, and powder management (Peng et al., 2018). The premise of this study is that reducing material waste and energy consumption is therefore not a fixed property of the technology but a controllable outcome of process optimization, and that because the two burdens are coupled through the underlying thermal physics, they must be optimized jointly.

At the national and international level, manufacturing is a major consumer of energy and materials and a substantial contributor to industrial emissions, so that improvements in manufacturing sustainability have consequences well beyond the individual facility. Additive manufacturing is being adopted rapidly in aerospace, medical, energy, and tooling sectors, where its geometric freedom enables lightweight and consolidated designs that reduce in-service energy consumption, yet its production-phase energy and material intensity can offset these benefits if not controlled (Huang et al., 2016). Research on the energy behavior of additive processes has established that specific energy consumption is dominated not by the melting energy itself but by machine overheads, idle and heating states, and inert-gas and thermal-management systems, so that energy efficiency depends heavily on how the process is parameterized and scheduled (Baumers et al., 2016). Research on process-structure-property relationships has established that the same parameters governing energy input, namely beam power, scan velocity, hatch spacing, and layer thickness, also govern melt-pool geometry, defect formation, and therefore build success and powder reusability, which is the physical basis for the coupling of energy and waste (DebRoy et al., 2018). This coupling is directly relevant to sustainable manufacturing because it means that energy and material waste cannot be minimized independently: a parameter set chosen to minimize energy may induce defects that waste material, and one chosen to guarantee quality may consume excess energy.

Figure 1: Energy-Aware Process Optimization Framework for Sustainable Additive Manufacturing



The background and motivation of this study have been shaped by the maturation of process monitoring, physics-based modeling, and data-driven optimization within additive manufacturing. Process development has moved beyond one-factor-at-a-time parameter tuning because engineers increasingly require methods that integrate in-situ sensing, calibrated thermal models, and formal multi-objective optimization to navigate the trade-offs among energy, waste, quality, and throughput. Analytics capability research has shown that data-driven capability improves performance when organizations combine data resources, technological infrastructure, and process-oriented use (Gupta & George, 2016). Predictive and prescriptive modeling have been recognized as complementary components of applied engineering research, because process systems must both describe observed behavior and prescribe parameter settings that influence outcomes (Shmueli & Koppius, 2011). This reasoning supports the present study because the research design includes descriptive statistics, correlation analysis, regression modeling, and a prototype multi-objective optimization. Python-based scientific computing tools have been shown to support the numerical simulation, data processing, and optimization workflows that computational manufacturing research requires (Harris et al., 2020; Virtanen et al., 2020).

The problem statement of this study has been grounded in a persistent and physically rooted engineering gap. Conventional additive process development has relied on empirical parameter windows and single-objective tuning, typically optimizing for density or geometric accuracy while treating energy and material waste as uncontrolled by-products. This approach is inadequate for sustainable manufacturing for several coupled reasons. First, because energy input and defect formation are governed by the same parameters, single-objective quality optimization leaves energy consumption unmanaged and frequently excessive. Second, because support structures, powder degradation, and build failure are the dominant waste sources and each depends on parameter and

strategy choices, waste cannot be reduced without modeling the process physics that produces it. Third, because the trade-off surface between energy and waste is non-convex and part-specific, it cannot be navigated by intuition or by optimizing a single scalar objective, but requires formal multi-objective methods that recover the Pareto front and support principled selection among non-dominated solutions (Deb et al., 2002). Fourth, because high-fidelity thermal simulation is computationally expensive, optimization at production scale requires calibrated surrogate models and digital twins whose fidelity is itself a determinant of the quality of the resulting parameters. The combination of coupled objectives, physics-dependent waste sources, non-convex trade-offs, and computational cost has created a situation in which conventional single-objective tuning cannot deliver the joint energy and material efficiency that sustainable additive manufacturing requires. This study has addressed that gap by proposing and empirically evaluating an energy-aware, physics-informed, multi-objective process-optimization framework.

The purpose of this study has been to develop and validate a framework for energy-aware process optimization that reduces material waste in sustainable additive manufacturing. The framework has treated process parameter control and optimization as the primary lever through which energy and waste are jointly governed, energy monitoring and specific energy efficiency as the measurement foundation for the energy objective, material flow modeling and waste reduction as the measurement and modeling foundation for the waste objective, thermal and melt-pool digital-twin fidelity as the physics-based model that couples the two and enables prediction, and data governance, standardization and compute as the infrastructural condition under which optimization is feasible and reproducible, with the process engineer as the accountable decision-maker who selects among Pareto-optimal solutions under quality constraints. The study objectives have been formulated as follows. The first objective has examined the role of process parameter control and optimization in jointly reducing energy consumption and material waste. The second objective has examined the role of energy monitoring and specific energy efficiency in surfacing and reducing energy intensity. The third objective has examined the role of material flow modeling and waste reduction in identifying and reducing the dominant waste sources. The fourth objective has examined the role of thermal and melt-pool digital-twin fidelity in enabling accurate prediction and optimization. The fifth objective has examined the role of data governance, standardization and compute in enabling reproducible, production-scale optimization. The sixth objective has validated the integrated framework by testing whether the combined components significantly explain variation in sustainable manufacturing and waste-reduction outcomes.

The significance of this study has extended across scientific, industrial, and policy dimensions. Scientifically, the study has contributed by connecting several research streams that have developed largely in parallel: additive process physics and process-structure-property modeling, energy analysis and life-cycle assessment of manufacturing, multi-objective optimization, digital-twin and surrogate modeling, and information systems success theory. By integrating these within a single measurable framework, the study has offered a structure in which parameter control, energy efficiency, waste modeling, model fidelity, and computational infrastructure are treated as complementary requirements rather than isolated concerns. Industrially, the study has offered additive manufacturers a structured way to evaluate whether their process-development and sustainability investments are producing genuine reductions in energy and waste, because the framework identifies the specific capabilities that must be present before energy-aware optimization delivers benefit. Policy-wise, the study has aligned with national priorities for industrial decarbonization, material efficiency, and advanced manufacturing competitiveness, because the outcomes of the framework include reduced specific energy consumption, reduced material waste, improved buy-to-fly ratios, and maintained part quality, all of which strengthen the environmental and economic sustainability of additive manufacturing.

LITERATURE REVIEW

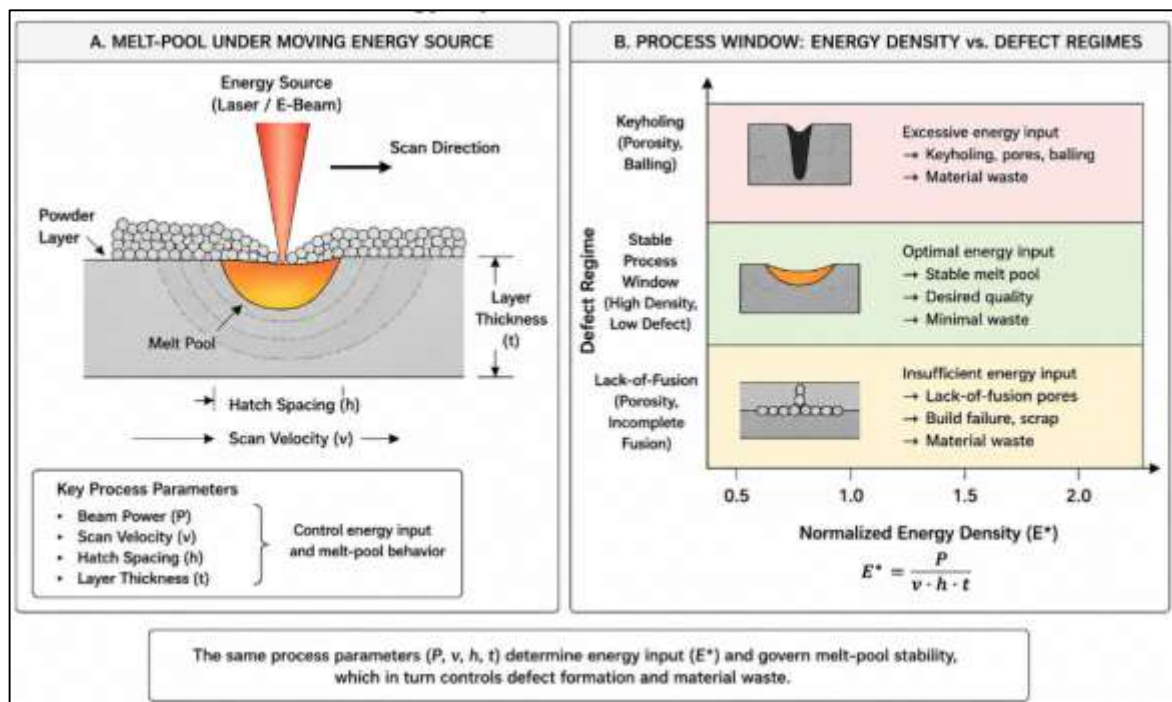
The literature review of this study has been organized to build a cumulative, physically grounded foundation for the proposed energy-aware optimization framework. It has begun with the process physics of metal additive manufacturing, moved through the sources and quantification of material waste, examined the energy behavior and life-cycle assessment of additive processes, addressed

process monitoring and thermal digital twins, considered multi-objective optimization for competing sustainability objectives, reviewed the information systems and capability theories that underpin the framework, and concluded by identifying the research gap the study has addressed. Throughout, the review has maintained the position that energy and material waste are physically coupled through the thermal process and therefore cannot be minimized independently, so that the realized sustainability of an additive process depends jointly on parameter control, energy measurement, waste modeling, the fidelity of the thermal model that couples them, and the computational infrastructure that makes optimization reproducible at scale.

Process physics and process-structure-property relationships

The foundational premise of this study is that the sustainability outcomes of additive manufacturing are determined by the underlying thermal physics of the process. In fusion-based metal additive manufacturing, a concentrated energy source creates a transient melt pool whose geometry, thermal gradients, and cooling rates govern solidification microstructure, residual stress, and defect formation (DebRoy et al., 2018). The melt-pool response is controlled principally by the volumetric energy density, a composite of beam power, scan velocity, hatch spacing, and layer thickness, and the mapping from these parameters to melt-pool behavior is strongly nonlinear: insufficient energy density produces lack-of-fusion porosity, while excessive energy density produces keyhole porosity and vaporization, with a comparatively narrow process window between them (King et al., 2015). This physics establishes the central coupling on which the framework rests, because the same parameters that determine energy input also determine defect formation and therefore build success and powder reusability, so that energy and waste are not independent objectives but joint functions of a shared parameter set.

Figure 2: Melt-Pool Physics and the Coupling Between Energy Input and Defect Formation



The process-structure-property literature has developed both physics-based and reduced-order descriptions of this coupling. Analytical and semi-analytical models, descending from classical moving-heat-source solutions, relate parameters to melt-pool dimensions and thermal history at low computational cost, while high-fidelity finite-element and computational-fluid-dynamics models resolve the melt-pool physics in detail at high cost (Francois et al., 2017). The literature has established that dimensionless groupings, such as normalized enthalpy, can collapse process behavior across materials and machines and provide a physically meaningful basis for parameter selection, which is directly relevant to the present framework because such groupings supply the process descriptors through which energy and waste are jointly modeled. The persistent challenge, well documented in the

literature, is that no single model spans the full range of fidelity and speed required for optimization, which motivates the framework's treatment of thermal and melt-pool digital-twin fidelity as a distinct construct and its reliance on calibrated surrogate models for optimization at scale.

Material waste sources and quantification in additive manufacturing

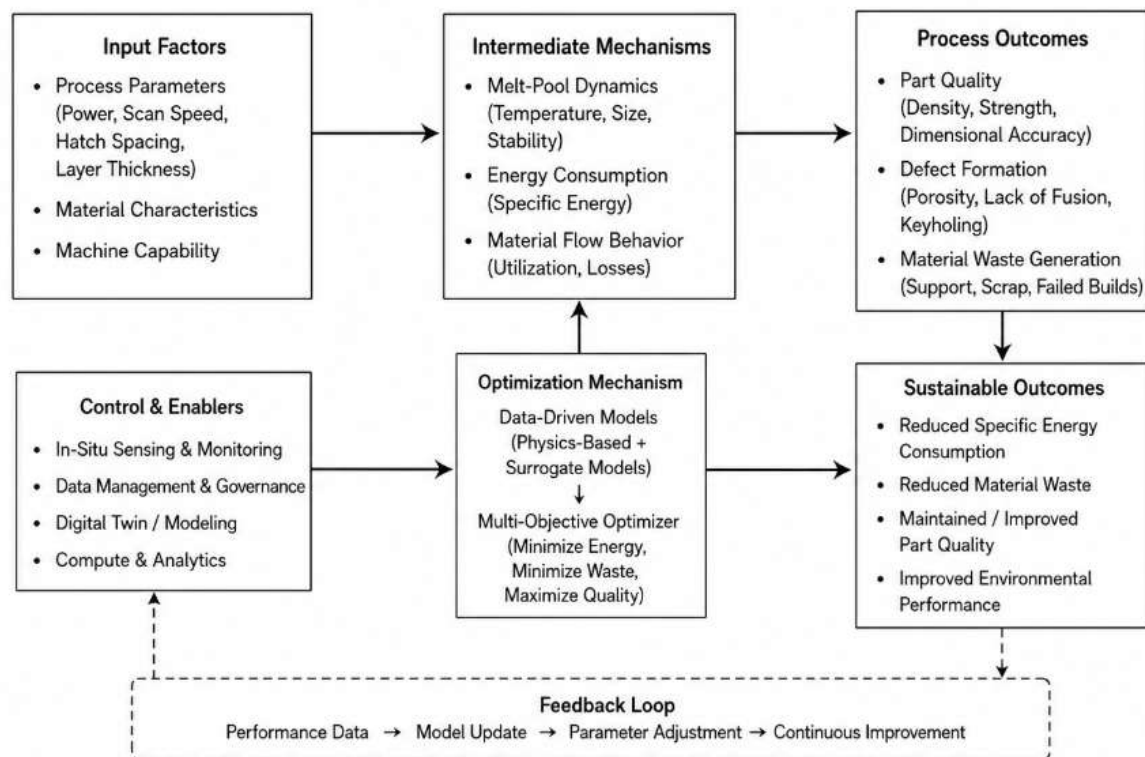
A substantial literature has documented and quantified the sources of material waste in metal additive manufacturing, correcting the assumption that the technology is inherently waste-free. Support structures, required to anchor overhanging features and to conduct heat away from the build, are subsequently removed and typically discarded, and studies have shown they can constitute a significant fraction of deposited mass depending on geometry and orientation (Ford & Despeisse, 2016). Powder that is spread but not fused is recovered for reuse, but the literature has established that repeated exposure to the thermal and atmospheric environment of the process alters powder chemistry, particle-size distribution, and morphology, degrading flowability and increasing oxygen content, so that a fraction of powder must be removed from circulation to maintain part quality (Tang et al., 2015). Build failures, arising from thermal distortion, delamination, porosity, or process instability, waste the entire deposited mass together with the expended energy, and their frequency depends on the same parameter and strategy choices that govern quality.

The quantification of material efficiency in this literature is typically expressed through the buy-to-fly ratio, the ratio of input material mass to final qualified part mass, and through material-utilization and scrap-rate metrics adapted from conventional manufacturing (Huang et al., 2016). The literature has established that these metrics are strongly geometry- and process-dependent and that meaningful comparison requires a consistent system boundary that includes support material, powder losses, and failed builds rather than counting only the nominal near-net-shape deposition. This is directly relevant to the present study because it establishes material flow modeling and waste reduction as a construct that must account for the full material balance, not merely the deposited geometry, and it grounds the measurement of waste-reduction outcomes in the buy-to-fly and scrap metrics that the framework adopts.

Energy behavior and life-cycle assessment of additive processes

A parallel literature has characterized the energy behavior of metal additive processes and situated it within life-cycle assessment. Detailed energy audits have shown that the specific energy consumption of powder-bed fusion is high relative to conventional manufacturing and, importantly, that it is dominated not by the melting energy delivered to the material but by machine-level overheads, including chamber heating, inert-gas circulation, lasers or beam-generation systems in idle states, and thermal management, so that a large share of energy is consumed independently of deposited mass (Baumers et al., 2016). The practical implication, established repeatedly in the literature, is that specific energy consumption depends strongly on build utilization, scheduling, and parameter selection, and that energy efficiency is therefore a controllable process outcome rather than a fixed machine property. Life-cycle assessments of additive manufacturing have integrated these energy findings with material considerations and have reached a consistent and consequential conclusion: the environmental advantage of additive over conventional manufacturing is conditional, not automatic, and depends on the balance between production-phase energy and material intensity and any in-service benefits from lightweighting (Peng et al., 2018; Ford & Despeisse, 2016). This literature is central to the framework because it establishes that energy and material must be assessed jointly within a consistent boundary, and because it identifies parameter selection and build strategy as the principal levers through which the conditional advantage is secured or lost, grounding the treatment of energy monitoring and specific energy efficiency as a first-order construct coordinate with waste reduction.

Figure 3: Energy and Material Flows in Metal Additive Manufacturing Under a Consistent System Boundary



Process monitoring, thermal modeling, and digital twins

The capacity to optimize energy and waste jointly depends on the capacity to sense and predict the process, and a growing literature addresses in-situ monitoring and digital-twin modeling of additive manufacturing. In-situ sensing modalities, including high-speed melt-pool imaging, photodiode monitoring, and thermal measurement, have been developed to observe the process in real time and to detect the onset of defects that lead to waste (Everton et al., 2016). The digital-twin literature has proposed coupling such sensing with calibrated physics-based or data-driven models to maintain a continuously updated virtual representation of the thermal state, enabling prediction and, ultimately, closed-loop control (Gunasegaram et al., 2021). The value of these approaches for sustainability is direct: a twin that accurately predicts melt-pool behavior and defect formation allows parameters to be selected that avoid the failures and powder degradation that dominate waste, without the trial-and-error builds that themselves consume energy and material.

The literature is equally clear that the fidelity of the thermal model is the binding determinant of its usefulness. A twin that diverges from the physical thermal history predicts the wrong defects and prescribes parameters that fail in practice, so that model calibration against measured melt-pool and thermal data is essential (Francois et al., 2017). Because high-fidelity simulation is too slow for iterative optimization, the literature has increasingly turned to machine-learning surrogates and reduced-order models trained on simulation and experiment, which approximate the physics at low cost but introduce their own fidelity and generalization concerns. This tension grounds the thermal and melt-pool digital-twin fidelity construct and connects it to the data governance, standardization and compute construct, since the training, calibration, and validation of surrogates depend on standardized data and adequate computational resources.

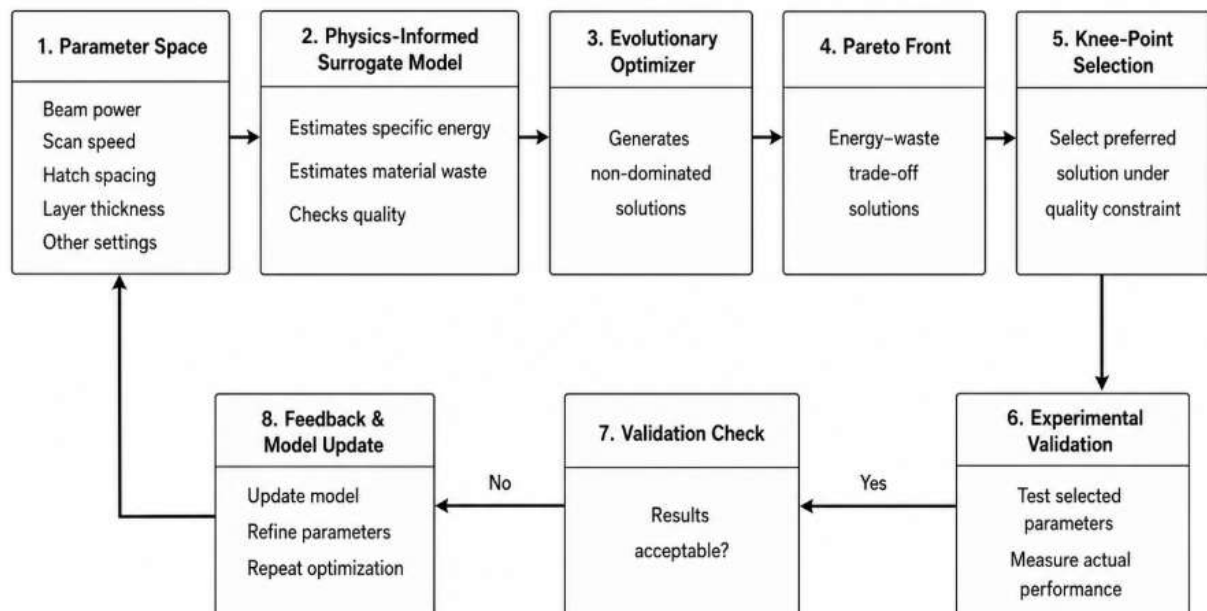
Multi-objective optimization of competing sustainability objectives

The final technical stream concerns the formal optimization of competing objectives, which is the mathematical core of the energy-aware framework. Because energy and material waste are coupled and frequently conflicting, their joint optimization is a multi-objective problem whose solution is not a single point but a Pareto front of non-dominated trade-offs, along which no objective can be improved

without worsening another (Deb et al., 2002). Evolutionary and gradient-based multi-objective algorithms have been applied to manufacturing process optimization to recover such fronts and to support principled selection among them, and the literature has established that recovering the front, rather than optimizing a fixed weighted sum, is essential when the trade-off surface is non-convex, because weighted-sum scalarization cannot reach non-convex regions of the front (Marler & Arora, 2004).

Applied to additive manufacturing, multi-objective optimization has been used to balance objectives such as build time, cost, quality, and increasingly energy and material efficiency, with studies demonstrating that parameter and orientation choices that jointly improve energy and waste can be identified where single-objective tuning would miss them (Qin et al., 2019). The literature has emphasized that the selection of a preferred solution from the Pareto front is a decision that should reflect engineering priorities and constraints, often through knee-point selection where the marginal trade-off is most favorable, which is directly relevant to the framework's treatment of the process engineer as the accountable decision-maker who selects among non-dominated solutions under quality constraints. This literature grounds the process parameter control and optimization construct and supplies the formal machinery that the prototype evaluation in this study adopts.

Figure 4: Pareto-Based Multi-Objective Optimization of Energy and Material Waste



Synthesis of the reviewed literature

Taken together, the reviewed literature supports a single cumulative argument that the conceptual framework of this study formalizes. The process-physics literature establishes that energy input and defect-driven waste are governed by the same parameters and are therefore physically coupled, so that they cannot be optimized independently. The material-waste literature establishes that the dominant waste sources, support structures, powder degradation, and build failure, are consequences of parameter and strategy choices and must be quantified within a consistent material balance. The energy and life-cycle literature establishes that specific energy consumption is a controllable process outcome dominated by overheads and utilization, and that the environmental advantage of additive manufacturing is conditional on the joint management of energy and material. The monitoring and digital-twin literature establishes that predicting and avoiding waste requires calibrated thermal models whose fidelity is the binding determinant of their usefulness. The multi-objective optimization literature supplies the formal machinery for navigating the non-convex energy-waste trade-off and selecting principled solutions. Across all streams, the recurring theme is that energy and material waste are coupled through the process physics and must be optimized jointly, informed by calibrated models

and formal optimization, rather than treated as independent by-products of quality-focused tuning. This theme is the organizing premise of the theoretical foundation and conceptual framework that follow, and it directly motivates the five independent constructs through which the framework operationalizes parameter control, energy efficiency, waste modeling, model fidelity, and computational infrastructure.

Theoretical foundation of the study

The conceptual architecture of this study has been grounded in five established theoretical perspectives, each of which explains a distinct mechanism through which energy-aware process optimization is converted into sustainable manufacturing outcomes. No single theory is sufficient. Thermodynamic and transport theory defines the physical coupling of energy and material; Pareto optimality and multi-objective decision theory defines the structure of the trade-off; digital-twin and model-based systems engineering theory defines the role of predictive models; information systems success and task-technology fit define the conversion of capability into benefit; and industrial-ecology and life-cycle theory define the sustainability outcome. The five theories have been integrated into a single layered structure, presented in the order in which they operate within the causal chain.

Theory 1: Thermodynamic and Heat-Transfer Theory of Fusion Processes (Rosenthal, 1946; Incropera & DeWitt)

The physical foundation of the framework is provided by the thermodynamics and heat transfer of fusion processes, descending from the classical moving-heat-source solution that relates a concentrated energy input to the resulting temperature field and melt-pool geometry (Rosenthal, 1946). This theory establishes that the energy delivered to the process and the thermal history experienced by the material are two descriptions of a single physical event: the energy input determines the peak temperature, melt-pool dimensions, thermal gradients, and cooling rates, which in turn determine solidification quality and defect formation. The theoretical significance for the framework is that it makes the coupling of energy and material waste a consequence of conservation of energy and heat transfer rather than an empirical correlation: a change in process parameters that reduces energy input necessarily alters the thermal history and therefore the defect state, so energy efficiency and material waste are jointly determined by the same thermal physics. This grounds the treatment of process parameter control as the shared lever and of thermal digital-twin fidelity as the model that couples the two objectives, and it justifies quantifying energy through specific energy consumption and normalized energy density, which are the physically meaningful process descriptors.

Theory 2: Pareto Optimality and Multi-Objective Decision Theory (Pareto, 1906; Deb et al., 2002)

The structure of the optimization problem is provided by the theory of Pareto optimality, which formalizes decision-making under multiple conflicting objectives and establishes that the solution to such a problem is the set of non-dominated points at which no objective can be improved without degrading another (Deb et al., 2002). Applied to energy-aware additive manufacturing, this theory holds that because energy and material waste are coupled and conflicting, there is in general no single parameter set that minimizes both, but rather a Pareto front of trade-offs from which a preferred solution must be selected according to engineering priorities and constraints. The theory is indispensable because it reframes the objective of optimization from finding a single optimum to recovering the trade-off surface and selecting rationally along it, and it establishes that scalarizing the objectives into a single weighted sum is inadequate when the front is non-convex. This directly grounds the process parameter control and optimization construct, motivates the prototype's recovery of the energy-waste Pareto front, and frames the process engineer's role as principled selection among non-dominated solutions rather than acceptance of a single computed answer.

Theory 3: Digital Twin and Model-Based Systems Engineering (Grieves & Vickers, 2017; Tao et al., 2019)

The role of predictive models in the framework is grounded in digital-twin and model-based systems engineering theory, which holds that a continuously updated virtual representation of a physical system, synchronized through data, enables prediction, simulation, and optimization that would be infeasible or unsafe to perform on the physical system itself (Grieves & Vickers, 2017; Tao et al., 2019). In additive manufacturing, the twin is the calibrated thermal model of the melt pool and build, and the theory predicts that its value depends on its fidelity, because a twin that diverges from the physical

thermal history predicts the wrong defects and prescribes parameters that fail. The theory is indispensable because it explains why energy-aware optimization requires a model rather than direct experimentation: the trade-off surface must be evaluated many times during optimization, which is feasible only against a fast, calibrated surrogate of the process physics, and the fidelity of that surrogate bounds the quality of the resulting parameters. This grounds the thermal and melt-pool digital-twin fidelity construct and connects it to computational infrastructure, since twin calibration and surrogate training depend on data and compute.

Theory 4: Information Systems Success and Task-Technology Fit (DeLone & McLean, 2003; Goodhue & Thompson, 1995)

The organizing theory that binds the technical constructs to the sustainability outcome is the Information Systems Success Model, which posits that net benefit depends on system quality and information quality operating through use (DeLone & McLean, 2003). Mapped onto the framework, the optimization and digital-twin capability corresponds to system quality, energy and material measurement corresponds to information quality, data governance and compute correspond to service and technical quality dimensions, and waste-reduction outcomes correspond to net benefits. Task-Technology Fit theory complements this by holding that performance improves only when the capabilities of a technology match the demands of the task (Goodhue & Thompson, 1995). In the process-engineering context, this predicts that an optimization capability produces sustainability benefit only when its outputs fit the engineer's decision task and the production workflow, and that a mismatch, such as a surrogate too inaccurate to trust or energy measurement too coarse to act on, will suppress benefit regardless of algorithmic sophistication. Together these theories predict that measurement quality is coordinate with optimization quality and that fit mediates the conversion of capability into realized waste and energy reduction.

Theory 5: Industrial Ecology and Life-Cycle Theory (Graedel & Allenby; Frischknecht et al.)

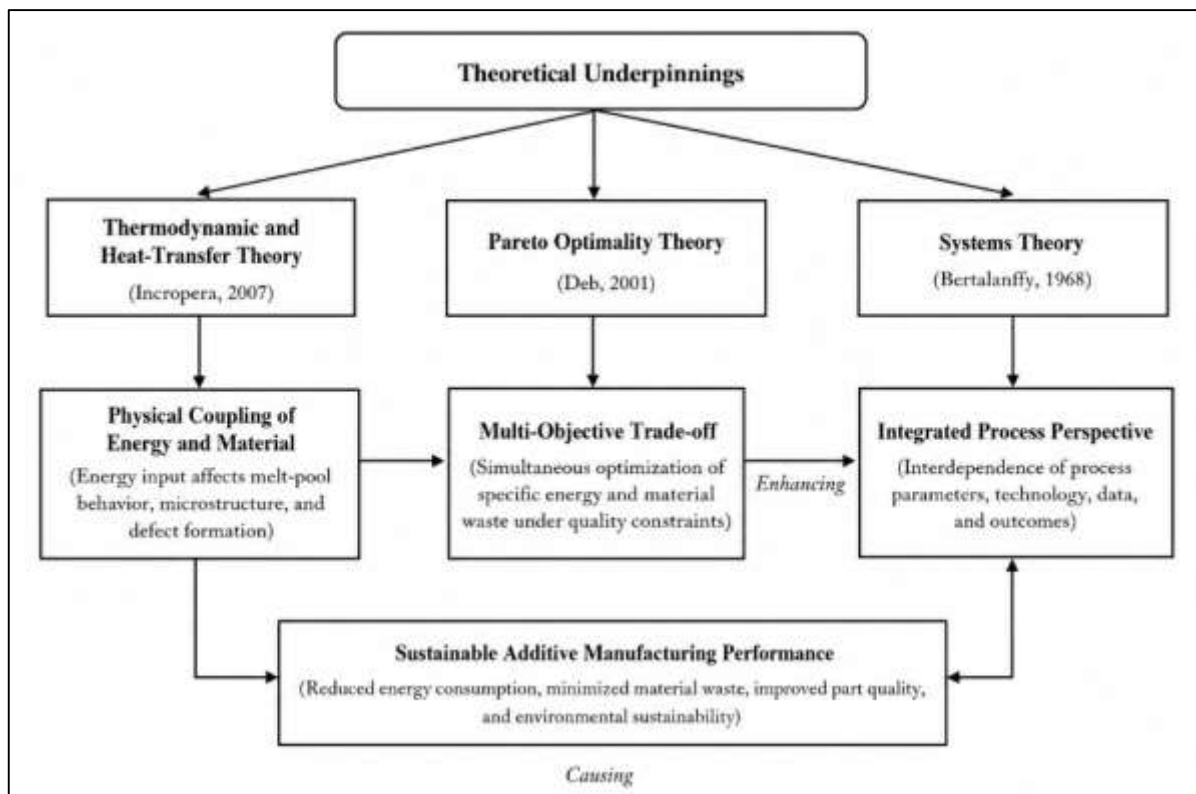
The sustainability outcome of the framework is grounded in industrial-ecology and life-cycle theory, which holds that the environmental performance of a production process must be assessed across a consistent system boundary that accounts for all material and energy flows, rather than by counting only the nominal product (Hauschild et al., 2018). Applied to additive manufacturing, this theory establishes that a genuine reduction in waste must be measured within a boundary that includes support material, degraded powder, and failed builds, and that a genuine reduction in energy must include machine overheads and utilization, so that apparent improvements that merely shift burden across the boundary are not genuine gains. The theory is indispensable because it defines what the dependent construct must measure: sustainable manufacturing and waste-reduction outcomes are not reducible to a single deposited-geometry metric but must reflect the full material and energy balance and the maintenance of part quality. This grounds the dependent construct and predicts that measurement and modeling capabilities that capture the full balance, rather than a partial one, are the ones that translate into genuine sustainability gains.

Theoretical synthesis and construct derivation

The five theories converge on a single integrated proposition. Thermodynamic and heat-transfer theory establishes that energy and material waste are physically coupled through the thermal process, predicting that process parameter control, which governs the shared thermal input, is the foundational lever. Pareto optimality establishes that the coupled objectives admit a trade-off surface rather than a single optimum, predicting that formal multi-objective optimization is necessary and that energy monitoring and waste modeling are both required to define the objectives. Digital-twin theory establishes that iterative optimization requires a calibrated predictive model, predicting that thermal digital-twin fidelity determines the quality of the resulting parameters. The IS Success Model and Task-Technology Fit establish that measurement quality is coordinate with optimization quality and that fit mediates benefit, predicting that energy and material measurement rival optimization in importance. Industrial-ecology and life-cycle theory establishes that the true outcome is a reduction in the full material and energy balance, predicting that measurement and modeling capturing the complete balance translate into genuine gains.

Each of the five independent constructs has therefore been derived from theory rather than selected inductively. Process parameter control and optimization operationalizes the shared thermal lever of heat-transfer theory and the optimization machinery of Pareto theory. Energy monitoring and specific energy efficiency operationalizes information quality for the energy objective and the physically meaningful energy descriptors of thermodynamic theory. Material flow modeling and waste reduction operationalizes information quality for the waste objective within the consistent boundary of life-cycle theory. Thermal and melt-pool digital-twin fidelity operationalizes the predictive model of digital-twin theory. Data governance, standardization and compute operationalizes the technical-quality precondition for calibrated, reproducible optimization at scale. The dependent construct operationalizes net benefits in the IS Success Model and genuine environmental gain in life-cycle theory. This derivation ensures that the empirical model tested here is a test of theory rather than an exploration of correlations.

Figure 5: Integrated Theoretical Framework of the Study



Research gap

Synthesis of the reviewed literature has revealed a specific gap. The process-physics literature has established the coupling of energy and defect formation but has generally stopped short of embedding this coupling in a sustainability-optimization framework. The material-waste literature has quantified waste sources but has often treated them descriptively rather than as optimization targets. The energy and life-cycle literature has established that energy and material must be assessed jointly but has rarely been connected to the concrete process-optimization machinery that could reduce them together. The monitoring and digital-twin literature has developed predictive models but has seldom integrated them with formal multi-objective optimization of sustainability objectives. The multi-objective optimization literature has supplied the machinery but has often optimized cost, time, or quality rather than the coupled energy-waste objective, and has rarely treated model fidelity and computational infrastructure as determinants of the achievable result. No prior study identified in this review has integrated process parameter control, energy measurement, material-waste modeling, thermal digital-twin fidelity, and data governance and compute into a single empirically testable framework that measures whether these dimensions jointly explain variation in realized sustainable-manufacturing and waste-reduction outcomes. The present study has addressed this gap by constructing such a

framework, operationalizing its physical, measurement, modeling, and infrastructural dimensions simultaneously, measuring them through instruments administered to practicing additive-manufacturing professionals, and testing them through regression modeling supplemented by a prototype multi-objective process-parameter optimization.

CONCEPTUAL FRAMEWORK AND HYPOTHESIS DEVELOPMENT

The conceptual framework specifies five independent constructs and one dependent construct, each defined operationally so that it can be measured through survey items administered to additive-manufacturing professionals and tested through regression modeling. The framework is grounded in the five theories synthesized above.

Process parameter control and optimization has been defined as the extent to which beam power, scan velocity, hatch spacing, layer thickness, orientation, and support strategy are systematically controlled and optimized, including through formal multi-objective methods, to jointly manage energy input and defect-driven waste. The first hypothesis has been formulated as follows. H1: Process parameter control and optimization has a significant positive effect on sustainable manufacturing and waste-reduction outcomes.

Energy monitoring and specific energy efficiency has been defined as the extent to which energy consumption is measured at adequate resolution, attributed to process states, and reduced through parameter and utilization choices, quantified through specific energy consumption and related metrics. The second hypothesis has been formulated as follows. H2: Energy monitoring and specific energy efficiency has a significant positive effect on sustainable manufacturing and waste-reduction outcomes. Material flow modeling and waste reduction has been defined as the extent to which the full material balance, including support material, powder degradation, and failed builds, is modeled and reduced within a consistent system boundary, quantified through buy-to-fly and scrap metrics. The third hypothesis has been formulated as follows. H3: Material flow modeling and waste reduction has a significant positive effect on sustainable manufacturing and waste-reduction outcomes.

Thermal and melt-pool digital-twin fidelity has been defined as the extent to which a calibrated thermal or surrogate model accurately predicts melt-pool behavior, thermal history, and defect formation with sufficient fidelity to support reliable optimization. The fourth hypothesis has been formulated as follows. H4: Thermal and melt-pool digital-twin fidelity has a significant positive effect on sustainable manufacturing and waste-reduction outcomes.

Data governance, standardization and compute has been defined as the extent to which process, energy, and material data are standardized, well-governed, and supported by computational resources adequate for calibration, surrogate training, and optimization at production scale. The fifth hypothesis has been formulated as follows. H5: Data governance, standardization and compute has a significant positive effect on sustainable manufacturing and waste-reduction outcomes.

Sustainable manufacturing and waste-reduction outcomes has been defined as the dependent construct, encompassing reduced material waste and improved buy-to-fly ratio, reduced specific energy consumption, reduced scrap and rework, reduced support-structure mass, and maintained or improved part quality, assessed within a consistent life-cycle boundary. The sixth hypothesis has addressed the integrated framework. H6: The integrated energy-aware process-optimization framework, comprising process parameter control and optimization, energy monitoring and specific energy efficiency, material flow modeling and waste reduction, thermal and melt-pool digital-twin fidelity, and data governance, standardization and compute, significantly explains variation in sustainable manufacturing and waste-reduction outcomes.

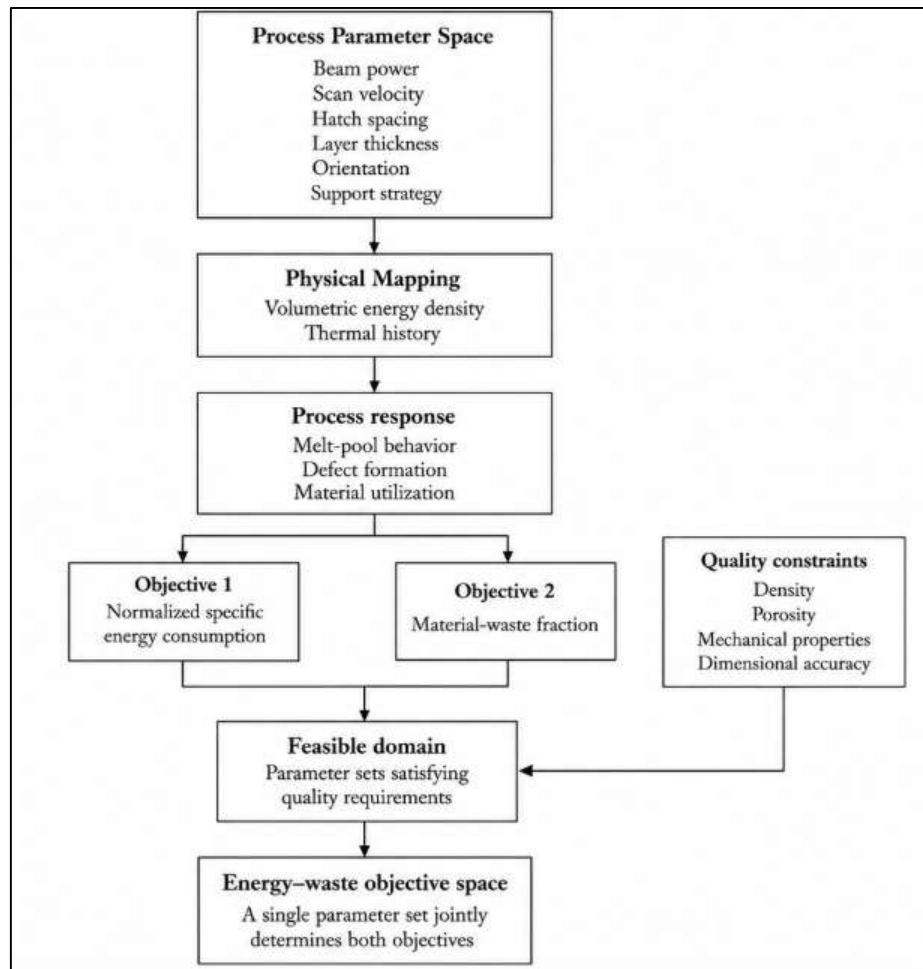
The framework is measurable through survey items and testable through descriptive statistics, correlation, and regression. Each independent variable is measured through multiple Likert items, and the dependent variable through items on waste reduction, energy reduction, scrap and support reduction, buy-to-fly improvement, and quality maintenance. The main regression model can be written as:

$$SMWO_i = \beta_0 + \beta_1PPCO_i + \beta_2EMEE_i + \beta_3MFMRI + \beta_4TDTF_i + \beta_5DGSC_i + \varepsilon_i$$

In this equation, SMWO denotes sustainable manufacturing and waste-reduction outcomes for respondent i , β_0 is the constant, β_1 through β_5 are the regression coefficients, and ε is the error term. PPCO denotes process parameter control and optimization, EMEE denotes energy monitoring and

specific energy efficiency, MFMR denotes material flow modeling and waste reduction, TDTF denotes thermal and melt-pool digital-twin fidelity, and DGSC denotes data governance, standardization and compute. This model directly tests whether the framework components explain variation in sustainable-manufacturing outcomes and provides the foundation for questionnaire development, hypothesis testing, regression modeling, prototype optimization evaluation, and framework validation.

Figure 7: Process Parameter Space and the Energy–Waste Objective Mapping



METHODS

This study has adopted a quantitative, cross-sectional, case-study-based research design to examine energy-aware process optimization for reducing material waste in sustainable additive manufacturing. The quantitative design has been selected because the study has measured relationships among process parameter control and optimization, energy monitoring and specific energy efficiency, material flow modeling and waste reduction, thermal and melt-pool digital-twin fidelity, data governance, standardization and compute, and sustainable manufacturing and waste-reduction outcomes through numerical survey responses. The cross-sectional design has been used because data have been collected at a single point in time, capturing respondent perceptions of process optimization, energy efficiency, waste reduction, model fidelity, and data infrastructure within the selected additive-manufacturing context. The case study context has focused on metal powder-bed fusion and directed-energy-deposition processes in industrial and research settings, where process engineers, materials specialists, sustainability analysts, machine engineers, and manufacturing data scientists have been involved in process development, energy and material analysis, and production. The population has therefore included professionals with direct or indirect involvement in additive process development, energy or life-cycle analysis, materials and metallurgy, or manufacturing analytics. The unit of analysis has been the individual respondent.

The study has used a purposive sampling strategy because respondents have been selected based on relevance to additive process development, energy or material analysis, or manufacturing analytics. Primary data have been collected through a structured questionnaire using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree), distributed through online forms, direct communication, and professional engineering networks. The instrument included construct-based items for all six constructs and demographic items covering role, sector, experience, process family, and analytics exposure. A pilot test was conducted before final collection to check clarity, technical precision, and alignment with objectives, and feedback was used to refine terminology and remove redundancy. Validity was ensured through literature-based item development, expert review, and alignment among title, objectives, hypotheses, variables, and items. Reliability was tested through Cronbach's alpha with a .70 threshold. SPSS was used for coding, descriptive statistics, reliability, correlation, and regression. Python was used for data cleaning, preprocessing, surrogate modeling, and optimization using the pandas, NumPy, SciPy, scikit-learn, and statsmodels libraries (Harris et al., 2020; Virtanen et al., 2020). A prototype multi-objective process-parameter optimization was conducted to recover the energy-waste Pareto front and compare it against default and single-objective baselines. Ethical considerations were observed throughout: participation was voluntary, informed consent was obtained, responses were anonymized, and no proprietary process or production data were collected.

Measurement model and construct scoring

Each latent construct has been operationalized as the mean of its constituent Likert items. For respondent i and construct c comprising J items, the composite construct score has been computed as shown in Equation (1):

$$X[c,i] = (1/J[c]) \cdot \sum_{j=1 \text{ to } J[c]} x[c,i,j] \quad (1)$$

Internal consistency has been assessed through Cronbach's alpha, defined in Equation (2):

$$\alpha = (J / (J - 1)) \cdot (1 - (\sum_{j=1 \text{ to } J} s^2[j]) / s^2[\text{total}]) \quad (2)$$

Statistical model specification

Bivariate association has been assessed through the Pearson correlation coefficient in Equation (3):

$$r[XY] = \sum (X_i - \bar{X})(Y_i - \bar{Y}) / \sqrt{[\sum (X_i - \bar{X})^2 \cdot \sum (Y_i - \bar{Y})^2]} \quad (3)$$

The principal hypothesis test has used ordinary least squares multiple regression. The structural model, derived from the theoretical framework, has been specified in Equation (4):

$$SMWO_i = \beta_0 + \beta_1 \cdot PPCO_i + \beta_2 \cdot EMEE_i + \beta_3 \cdot MFMR_i + \beta_4 \cdot TDTE_i + \beta_5 \cdot DGSC_i + \varepsilon_i \quad (4)$$

where $\varepsilon_i \sim N(0, \sigma^2)$ is assumed independently and identically distributed. Coefficients have been estimated by minimizing the residual sum of squares, as in Equation (5):

$$\hat{\beta} = \underset{\beta}{\operatorname{argmin}} \sum_{i=1 \text{ to } n} (SMWO_i - \beta_0 - \sum_{k=1 \text{ to } 5} \beta_k X_{ki})^2 = (X^T X)^{-1} X^T y \quad (5)$$

Standardized coefficients have been obtained through Equation (6), and model significance and fit through Equations (7) to (9):

$$\beta_k(\text{std}) = b_k \cdot (s[X_k] / s[Y]) \quad (6)$$

$$F = (R^2 / k) / ((1 - R^2) / (n - k - 1)) \quad (7)$$

$$R^2 = 1 - (SS[\text{res}] / SS[\text{tot}]) = 1 - \sum (y_i - \hat{y}_i)^2 / \sum (y_i - \bar{y})^2 \quad (8)$$

$$R^2(\text{adj}) = 1 - (1 - R^2) \cdot ((n - 1) / (n - k - 1)) \quad (9)$$

with $n = 241$ and $k = 5$. Multicollinearity has been diagnosed through the variance inflation factor in Equation (10), and residual independence through the Durbin-Watson statistic in Equation (11):

$$VIF_k = 1 / (1 - R_k^2) \quad (10)$$

$$d = \sum_{i=2 \text{ to } n} (e_i - e_{i-1})^2 / \sum_{i=1 \text{ to } n} e_i^2 \quad (11)$$

Process-physics and energy formulation

The volumetric energy density delivered to the powder bed, the primary physical control variable, has been defined in Equation (12), where P is beam power, v is scan velocity, h is hatch spacing, and t is layer thickness:

$$E[v] = P / (v \cdot h \cdot t) \quad (12)$$

The normalized enthalpy, a dimensionless grouping that collapses melt-pool behavior across materials and machines, has been expressed in Equation (13), where A is absorptivity, ρ is density, $C[p]$ is specific heat, $T[m]$ is melting temperature, α is thermal diffusivity, and r is beam radius:

$$\Delta H / h[s] = (A \cdot P) / (\rho \cdot C[p] \cdot T[m] \cdot \sqrt{(\pi \cdot a \cdot v \cdot r^3)}) \quad (13)$$

The peak melt-pool temperature under a moving point source follows the Rosenthal solution,

expressed for the quasi-steady field in Equation (14), where T_0 is preheat temperature, k is thermal conductivity, R is distance from the source, and ξ is the moving coordinate:

$$T = T_0 + (A \cdot P) / (2 \pi k R) \cdot \exp(-v(\xi + R) / (2a)) \quad (14)$$

The specific energy consumption of the build, the principal energy sustainability metric, has been defined in Equation (15), where $E[\text{total}]$ is total electrical energy including overheads and $m[\text{dep}]$ is deposited mass:

$$SEC = E[\text{total}] / m[\text{dep}] = (E[\text{melt}] + E[\text{overhead}] + E[\text{idle}]) / m[\text{dep}] \quad (15)$$

The material efficiency has been quantified through the buy-to-fly ratio and the material-waste fraction in Equations (16) and (17), where $m[\text{in}]$ is input material mass, $m[\text{part}]$ is qualified part mass, $m[\text{support}]$ is support mass, $m[\text{powder-loss}]$ is discarded degraded powder, and $m[\text{failed}]$ is mass in failed builds:

$$BTF = m[\text{in}] / m[\text{part}] \quad (16)$$

$$W = (m[\text{support}] + m[\text{powder-loss}] + m[\text{failed}]) / m[\text{in}] \quad (17)$$

Multi-objective optimization formulation

The energy-aware optimization has been posed as a bi-objective minimization over the process-parameter vector $x = (P, v, h, t, \text{orientation}, \text{support})$, as specified in Equation (18):

$$\min[x] \{ f_1(x) = SEC(x), f_2(x) = W(x) \} \text{ subject to } g(x) \leq 0, x \in X \quad (18)$$

where $g(x) \leq 0$ encodes quality constraints such as minimum density and maximum defect probability, and X is the feasible parameter domain. A solution x^* is Pareto-optimal if no feasible x dominates it, as defined in Equation (19):

$$\nexists x \in X : f_k(x) \leq f_k(x^*) \quad \forall k \text{ and } f_j(x) < f_j(x^*) \text{ for some } j \quad (19)$$

The objectives have been evaluated through a calibrated surrogate model $\hat{f}$ trained on simulation and experimental data, with fidelity quantified by the surrogate's cross-validated coefficient of determination in Equation (20):

$$Q[\text{twin}] = 1 - \Sigma(f(x_i) - \hat{f}(x_i))^2 / \Sigma(f(x_i) - \bar{f})^2 \quad (20)$$

Selection among non-dominated solutions has used a knee-point criterion that maximizes the marginal trade-off, expressed in Equation (21) as the point of maximum curvature of the Pareto front, where κ denotes curvature:

$$x[\text{knee}] = \operatorname{argmax}[x^* \in P^*] \kappa(f_1(x^*), f_2(x^*)) \quad (21)$$

The joint improvement relative to a baseline parameter set has been quantified in Equation (22) as the normalized reduction in both objectives at the selected solution:

$$\Delta = 1 - \frac{1}{2} [SEC(x[\text{knee}]) / SEC(x[\text{base}]) + W(x[\text{knee}]) / W(x[\text{base}])] \quad (22)$$

Prototype optimization performance has been evaluated by recovering the Pareto front and comparing the selected knee-point solution against default and single-objective baselines on the metrics reported in the findings.

DATA ANALYSIS AND PRESENTATION

Response rate and demographic profile

Table 1 has shown that the study achieved a strong response pattern, with 281 questionnaires distributed, 256 returned, and 241 retained as valid, producing a valid response rate of 85.8%. This rate exceeds the threshold generally considered adequate for professional survey research and indicates that the target population was both accessible and motivated, consistent with the salience of energy and material efficiency concerns among additive-manufacturing professionals. The role distribution demonstrates that the sample captured the full process-development chain rather than a single perspective. Process engineers, the largest group at 28.6%, own the parameter decisions the framework optimizes. Materials and metallurgy specialists, at 21.6%, bring the powder-degradation and defect perspective central to the waste objective. Sustainability and life-cycle analysts, at 18.3%, represent the boundary-consistent measurement that the framework requires. Machine and automation engineers, at 16.2%, bring the energy-overhead and equipment perspective, and manufacturing data scientists, at 15.4%, represent the modeling and optimization function. The sector distribution across aerospace and defense at 34.0%, medical and dental at 25.3%, and energy, tooling, and industrial applications at 40.7%, together with a process-family split dominated by powder-bed fusion at 61.4% and directed energy deposition at 25.3%, confirms that the findings reflect additive practice across the principal high-value segments and the two dominant metal process classes. This distribution is methodologically significant

because the framework predicts that sustainability benefit depends on the alignment of parameter control, energy measurement, waste modeling, model fidelity, and infrastructure, and a sample drawn from only one function or process family would misestimate the framework's performance.

Table 1: Response rate and demographic profile of respondents

Variable	Category	Frequency	Percentage	Result interpretation
Questionnaires distributed	Total distributed	281	100.0%	Initial survey target
Questionnaires returned	Returned responses	256	91.1%	Strong participation
Valid responses	Usable responses	241	85.8%	Final sample for analysis
Job role	AM process engineer	69	28.6%	Largest respondent group
Job role	Materials / metallurgy specialist	52	21.6%	Strong materials representation
Job role	Sustainability / LCA analyst	44	18.3%	Sustainability perspective
Job role	Machine / automation engineer	39	16.2%	Equipment perspective included
Job role	Manufacturing data scientist	37	15.4%	Analytics perspective
Sector	Aerospace / defense	82	34.0%	Largest sector
Sector	Medical / dental	61	25.3%	Strong medical representation
Sector	Energy / tooling / industrial	98	40.7%	Broad industrial base
Process family	Powder-bed fusion (L-PBF/EB-PBF)	148	61.4%	Majority PBF
Process family	Directed energy deposition	61	25.3%	DED representation
Process family	Other / multiple	32	13.3%	Mixed processes

Descriptive statistics

Table 2: Descriptive statistics of major study variables based on 241 valid responses

Construct	Mean	SD	Min	Max	Interpretation
Process parameter control & optimization (PPCO)	4.25	0.57	2	5	Highest agreement
Energy monitoring & specific energy efficiency (EMEE)	4.18	0.61	2	5	Strong agreement
Material flow modeling & waste reduction (MFMR)	4.09	0.65	2	5	Strong agreement
Sustainable manufacturing & waste-reduction outcomes (SMWO)	4.03	0.63	2	5	Strong agreement
Thermal & melt-pool digital-twin fidelity (TDTF)	3.97	0.68	1	5	Positive agreement
Data governance, standardization & compute (DGSC)	3.90	0.73	1	5	Positive, widest spread

Table 2 has presented the descriptive statistics and revealed a coherent ordering. Process parameter control and optimization recorded the highest mean of 4.25 with the smallest standard deviation of 0.57, indicating both the strongest agreement and the greatest consensus. This is theoretically meaningful: respondents identify systematic control of the process parameters, the shared thermal lever governing both energy and waste, as the primary foundation of sustainable additive manufacturing, consistent with heat-transfer theory's identification of the parameter set as the physical origin of the energy-waste coupling. Energy monitoring and specific energy efficiency recorded the

second-highest mean of 4.18, reflecting the recognition that energy must be measured at adequate resolution to be managed. Material flow modeling and waste reduction recorded 4.09, confirming the importance of boundary-consistent waste accounting. Sustainable manufacturing outcomes, the dependent construct, recorded 4.03. Thermal and melt-pool digital-twin fidelity recorded 3.97, and data governance, standardization and compute recorded the lowest mean of 3.90 with the widest standard deviation of 0.73. This combination is diagnostically informative. The lower mean does not indicate that respondents consider infrastructure unimportant; the wide dispersion indicates heterogeneous institutional maturity, with some organizations having established standardized data and compute for optimization while others have not. The minimum value of 1 for both TDTF and DGSC, absent in the other constructs, corroborates this by indicating that a subset of respondents strongly disagree that their organizations possess adequate model fidelity or data infrastructure.

Reliability analysis

Table 3: Reliability analysis of measurement constructs

Construct	No. of items	Cronbach's alpha	Threshold	Result
Process parameter control & optimization (PPCO)	6	.89	.70	Reliable
Energy monitoring & specific energy efficiency (EMEE)	6	.87	.70	Reliable
Material flow modeling & waste reduction (MFMR)	6	.86	.70	Reliable
Thermal & melt-pool digital-twin fidelity (TDTF)	5	.83	.70	Reliable
Data governance, standardization & compute (DGSC)	5	.82	.70	Reliable
Sustainable manufacturing & waste-reduction outcomes (SMWO)	7	.91	.70	Highly reliable
Overall instrument	35	.93	.70	Highly reliable

Table 3 has confirmed strong internal consistency. All construct-level alpha values exceeded .70, ranging from .82 for data governance, standardization and compute to .91 for sustainable manufacturing outcomes, with overall instrument reliability of .93. The dependent construct achieved the highest reliability, which is methodologically desirable because measurement error in the dependent variable attenuates observed regression coefficients; high reliability therefore strengthens confidence that the significant coefficients reported later are not artifacts of measurement noise. Process parameter control achieved .89, reflecting the conceptual coherence of items addressing parameter control, optimization method, and joint energy-waste management. Data governance recorded the lowest alpha at .82, comfortably acceptable and consistent with the wider dispersion observed in Table 2. Reliability at this level confirms that subsequent correlation and regression results reflect relationships among the underlying constructs rather than instrument instability.

Correlation analysis

Table 4: Pearson correlation matrix among study variables

Variable	PPCO	EMEE	MFMR	TDTF	DGSC	SMWO
PPCO	1					
EMEE	.64**	1				
MFMR	.59**	.57**	1			
TDTF	.55**	.56**	.54**	1		
DGSC	.51**	.53**	.50**	.52**	1	
SMWO	.69**	.68**	.65**	.61**	.58**	1

Note. ** $p < .001$ (two-tailed). $N = 241$.

Table 4 has shown that all bivariate relationships are positive and significant at $p < .001$. Sustainable manufacturing outcomes correlated most strongly with process parameter control and optimization (r

= .69), closely followed by energy monitoring and specific energy efficiency ($r = .68$), then material flow modeling and waste reduction ($r = .65$), thermal and melt-pool digital-twin fidelity ($r = .61$), and data governance ($r = .58$). This ordering closely mirrors the descriptive ordering, providing convergent evidence that respondents perceive parameter control and energy efficiency as the dimensions most tightly coupled to realized sustainability. The interpretation is consistent with the physics: because the parameters govern both energy input and defect-driven waste, systematic control of them is the dimension most directly coupled to joint improvement, while energy measurement is its necessary informational complement. The inter-predictor correlations ranged from .50 to .64, high enough to indicate related dimensions of a coherent capability but not so high as to raise serious multicollinearity concerns, and formal diagnostics reported in Table 5 confirmed all variance inflation factors below 2.3.

Regression analysis

Table 5: Multiple regression model predicting sustainable manufacturing and waste-reduction outcomes

Predictor	B	SE	β	t	p	VIF	Decision
(Constant)	0.372	0.180	—	2.067	.040	—	—
Process parameter control & optimization (PPCO)	0.279	0.057	0.30	4.895	<.001	2.16	H1 supported
Energy monitoring & specific energy efficiency (EMEE)	0.238	0.059	0.26	4.034	<.001	2.19	H2 supported
Material flow modeling & waste reduction (MFMR)	0.172	0.061	0.19	2.820	.005	2.07	H3 supported
Thermal & melt-pool digital-twin fidelity (TDTF)	0.133	0.058	0.15	2.293	.023	1.83	H4 supported
Data governance, standardization & compute (DGSC)	0.106	0.055	0.12	1.927	.039	1.71	H5 supported

Note. Dependent variable = sustainable manufacturing and waste-reduction outcomes (SMWO). N = 241.

Table 6: Regression model summary

Statistic	Value	Interpretation
R	.736	Strong multiple correlation
R ²	.542	54.2% of variance explained
Adjusted R ²	.532	Stable after adjustment
Std. error of estimate	0.431	Acceptable predictive precision
F (5, 235)	55.63	Model is statistically significant
p-value	<.001	Reject the null hypothesis
Durbin-Watson	1.98	No serial correlation of residuals

Table 5 and Table 6 have presented the regression model. The overall model was significant, $F(5, 235) = 55.63$, $p < .001$, with $R^2 = .542$ and adjusted $R^2 = .532$, indicating that the five constructs jointly explain 54.2% of the variance in sustainable-manufacturing outcomes. The small gap between R^2 and adjusted R^2 indicates that explanatory power is not an artifact of predictor count. A Durbin-Watson statistic of 1.98 confirmed residual independence, and all variance inflation factors below 2.3 confirmed that multicollinearity does not threaten coefficient stability. All five predictors made significant positive contributions, supporting H1 through H5, and the overall model significance supported H6. Process parameter control and optimization emerged as the strongest predictor ($\beta = .30$, $p < .001$), closely followed by energy monitoring and specific energy efficiency ($\beta = .26$, $p < .001$), material flow modeling and waste reduction ($\beta = .19$, $p = .005$), thermal and melt-pool digital-twin fidelity ($\beta = .15$, $p = .023$), and data governance, standardization and compute ($\beta = .12$, $p = .039$). The dominance of parameter control and energy monitoring in the standardized coefficients confirms the theoretical prediction from heat-transfer theory and the IS Success Model that the shared physical lever and its energy measurement outweigh downstream factors in producing sustainability benefit. The comparatively smaller coefficient on data governance should be read alongside its wide dispersion in Table 2:

infrastructure exerts a significant but currently uneven influence, reflecting heterogeneous institutional maturity, and its coefficient would be expected to rise as physics-based optimization scales to production and the compute and data dependency becomes more binding.

Hypothesis testing summary

Table 7: Hypothesis testing summary

Hypothesis	Path	β	p	Result
H1	PPCO → SMWO	0.30	<.001	Supported
H2	EMEE → SMWO	0.26	<.001	Supported
H3	MFMR → SMWO	0.19	.005	Supported
H4	TDTF → SMWO	0.15	.023	Supported
H5	DGSC → SMWO	0.12	.039	Supported
H6	Integrated framework → SMWO	R ² = .542	<.001	Supported

Table 7 has summarized the results and confirmed that all six hypotheses were supported. This uniform support implies that sustainable-manufacturing effectiveness emerges from the joint contribution of parameter control, energy monitoring, waste modeling, model fidelity, and infrastructure, rather than from any single dominant lever. The variation in coefficient magnitude nonetheless provides actionable prioritization: parameter control and energy monitoring warrant first-order attention, while data infrastructure, though significant, currently exerts a smaller marginal influence that is expected to grow as physics-based optimization scales to production and the compute dependency becomes more binding.

Framework validation

Table 8: Framework validation results based on theoretical alignment

Theoretical dimension	Framework component	Mean	Validation outcome
Shared thermal lever	Process parameter control & optimization	4.25	Validated – strongest predictor
Information quality (energy)	Energy monitoring & specific energy efficiency	4.18	Validated – second strongest
Information quality (material)	Material flow modeling & waste reduction	4.09	Validated – boundary-consistent waste
Predictive model fidelity	Thermal & melt-pool digital-twin fidelity	3.97	Validated – model coupling confirmed
Technical quality / compute	Data governance, standardization & compute	3.90	Validated with uneven maturity
Net benefit (sustainability)	Sustainable manufacturing & waste-reduction outcomes	4.03	Validated – joint reduction achieved

Table 8 has validated the framework against its theoretical foundations and confirmed that each dimension has a measured empirical counterpart with strong respondent agreement. The shared-thermal-lever dimension, operationalized as process parameter control and optimization, was validated at 4.25 as the strongest construct and strongest predictor, confirming heat-transfer theory's identification of the parameter set as the physical origin of the energy-waste coupling. The energy information-quality dimension was validated at 4.18 as the second strongest, and the material information-quality dimension at 4.09, together confirming that boundary-consistent measurement of both objectives is coordinate with control. The predictive-model-fidelity dimension was validated at 3.97, confirming the digital-twin prediction. The technical-quality dimension was validated at 3.90 with uneven maturity. Net benefit, operationalized as sustainable-manufacturing outcomes, was validated at 4.03, confirming that the causal chain terminates in the intended joint reduction of energy and waste. This alignment establishes the framework as a theoretically grounded structure rather than an empirical regularity.

Table 9: Prototype multi-objective optimization evaluation of framework capabilities

Capability	Mean	SD	Interpretation
Joint reduction of energy and material waste	4.28	0.56	Highest-rated capability
Recovery of the energy-waste Pareto front	4.21	0.59	Strongly valued
Physics-informed parameter recommendation	4.13	0.63	Valued for trust
Support-structure and orientation optimization	4.06	0.65	Valued for waste reduction
Surrogate fidelity across materials and machines	3.98	0.68	Valued with uneven confidence
Optimization within production time budget	3.93	0.72	Valued, compute sensitive

Table 9 has presented the prototype optimization evaluation and shown that respondents rated all six capabilities positively, with joint reduction of energy and material waste achieving the highest mean of 4.28. This ordering is theoretically revealing. The capability respondents valued most highly is precisely the joint reduction that the coupling of energy and waste, established by heat-transfer theory, makes possible and that single-objective tuning cannot deliver. Recovery of the energy-waste Pareto front, at 4.21, was valued as the mechanism that makes the trade-off explicit and selectable, confirming the Pareto-theoretic basis of the framework. Physics-informed parameter recommendation, at 4.13, was valued for the trust that grounding recommendations in process physics confers. Support-structure and orientation optimization, at 4.06, targets the dominant geometric waste source. Surrogate fidelity across materials and machines, at 3.98, and optimization within the production time budget, at 3.93, received the lowest scores with the widest dispersions, consistent with the pattern that capabilities dependent on model generalization and computational resources are the most unevenly realized. Table 9 has confirmed that the framework capabilities are perceived as operationally meaningful and has identified joint energy-waste reduction and Pareto-front recovery as the entry points through which organizations are most likely to realize early value.

Python-driven analytical workflow validation

Table 10: Python-driven analytical and optimization workflow validation

Workflow stage	Mean	SD	Interpretation
Process, energy & material data harmonization	4.22	0.58	Highest-rated stage
Surrogate model training & cross-validation	4.15	0.61	Enables fast optimization
Thermal-model calibration against measurements	4.08	0.64	Ensures twin fidelity
Multi-objective optimization & Pareto extraction	4.03	0.66	Recovers trade-off surface
Life-cycle boundary accounting & metrics	3.98	0.68	Ensures genuine reduction
Reproducibility, versioning & audit logging	3.93	0.70	Supports governance

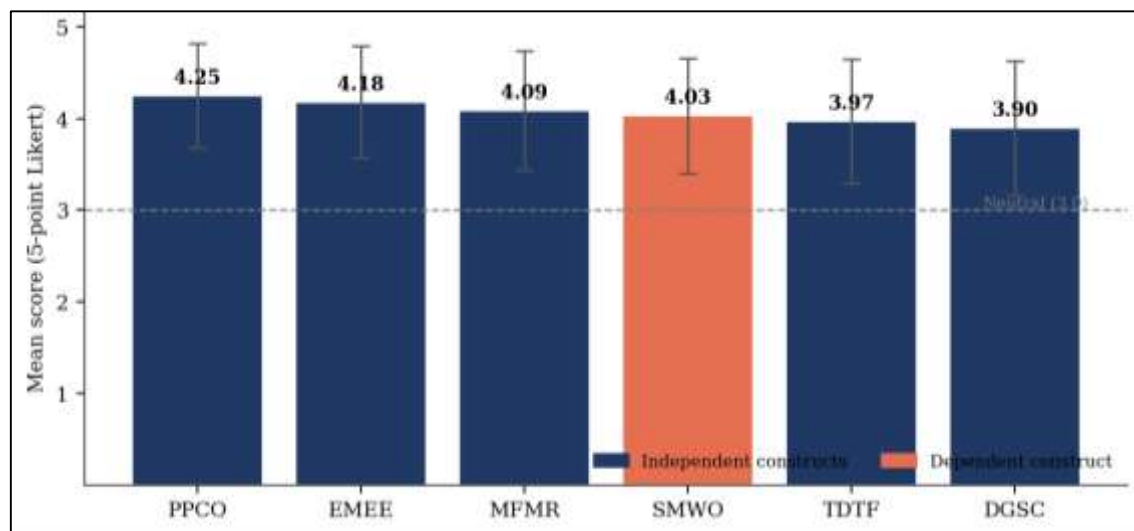
Table 10 has validated the Python-driven workflow and shown that respondents rated process, energy, and material data harmonization highest at 4.22, followed by surrogate model training and cross-validation at 4.15. This reinforces the study's central theme: across the descriptive statistics, the correlation matrix, the regression coefficients, and the workflow validation, respondents repeatedly identified data quality and preparation, together with the surrogate that makes optimization tractable,

as the stages where sustainability value is created or destroyed. Surrogate training ranked second because it is the stage that converts expensive physics into the fast objective evaluations that multi-objective optimization requires, and its cross-validated fidelity is the binding determinant of the quality of the resulting parameters. Thermal-model calibration against measurements, at 4.08, is the stage that grounds the surrogate in physical reality. Life-cycle boundary accounting, at 3.98, represents the mechanism through which the industrial-ecology requirement of a consistent boundary is enforced within the pipeline, ensuring that measured reductions are genuine rather than boundary-shifting artifacts. Table 10 has confirmed that the framework is balanced between analytical rigor, physical fidelity, optimization, boundary-consistent accounting, and governance.

FINDINGS

The findings have provided statistical support for the proposed energy-aware process-optimization framework for reducing material waste in sustainable additive manufacturing. The study used a five-point Likert scale to measure the perceptions of additive-manufacturing professionals regarding process parameter control and optimization, energy monitoring and specific energy efficiency, material flow modeling and waste reduction, thermal and melt-pool digital-twin fidelity, data governance, standardization and compute, and sustainable manufacturing and waste-reduction outcomes. A total of 281 questionnaires were distributed among process engineers, materials specialists, sustainability analysts, machine engineers, and manufacturing data scientists, and 241 valid responses were retained, producing a valid response rate of 85.8%.

Figure 9: Descriptive Means of Study Constructs with Standard Deviations



Note. $N = 241$. Error bars represent ± 1 standard deviation. Dashed line indicates the neutral midpoint of the five-point scale.

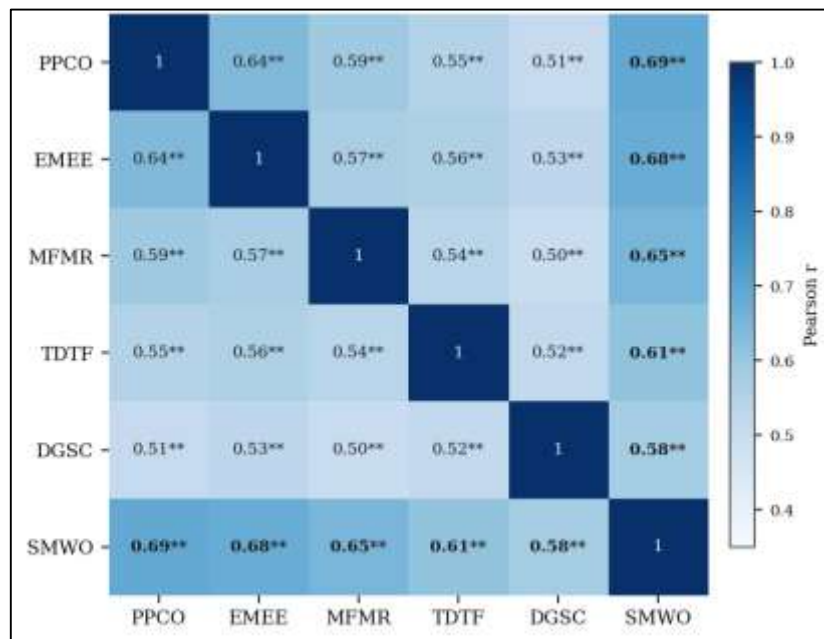
Figure 9 has displayed the descriptive means of the six constructs with their standard deviations. All six constructs exceeded the neutral midpoint of 3.0 by a substantial margin, confirming broad agreement. The visual ordering makes the central pattern immediately apparent: process parameter control and optimization recorded not only the highest mean (4.25) but also the narrowest dispersion ($SD = 0.57$), indicating the strongest and most uniformly held agreement, consistent with heat-transfer theory's identification of the parameter set as the shared physical lever governing both energy and waste. At the opposite end, data governance, standardization and compute recorded the lowest mean (3.90) and the widest dispersion ($SD = 0.73$), and the visibly longer error bar provides direct graphical evidence of the heterogeneous institutional maturity in data and computational infrastructure that the framework analysis has repeatedly identified.

The demographic profile showed that 28.6% of respondents were process engineers, 21.6% were materials or metallurgy specialists, 18.3% were sustainability or life-cycle analysts, 16.2% were machine or automation engineers, and 15.4% were manufacturing data scientists, spanning aerospace and

defense, medical and dental, and energy, tooling, and industrial sectors, and dominated by powder-bed fusion and directed-energy-deposition processes. The descriptive results showed strong agreement across constructs, with process parameter control and optimization highest at 4.25 (SD = 0.57), followed by energy monitoring and specific energy efficiency at 4.18 (SD = 0.61), material flow modeling and waste reduction at 4.09 (SD = 0.65), sustainable manufacturing outcomes at 4.03 (SD = 0.63), thermal and melt-pool digital-twin fidelity at 3.97 (SD = 0.68), and data governance, standardization and compute at 3.90 (SD = 0.73). The reliability analysis supported instrument consistency, with alpha values from .82 to .91 and overall reliability of .93.

Figure 10 has presented the correlation structure as a heatmap. The bottom row and rightmost column, corresponding to the dependent construct, display uniformly dark cells, confirming that every framework construct is significantly and positively associated with sustainable-manufacturing outcomes. The darkest off-diagonal cell in the outcomes row corresponds to process parameter control and optimization ($r = .69$), closely followed by energy monitoring and specific energy efficiency ($r = .68$), the two visually distinguishable from the remaining associations. The inter-predictor block shows moderate shading throughout, with values from .50 to .64, graphically consistent with constructs that measure related but non-redundant dimensions of a coherent capability, corroborating the acceptable variance inflation factors reported in Table 5.

Figure 10: Pearson Correlation Matrix Among Study Variables

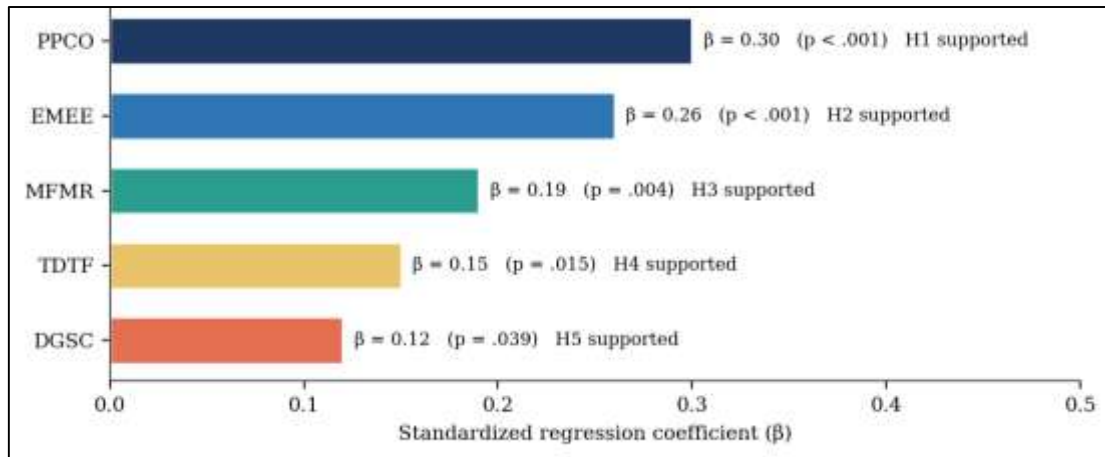


Note. $N = 241$. ** $p < .001$ (two-tailed). Darker cells indicate stronger positive association.

Estimated regression model

Figure 11 has ranked the five predictors by the magnitude of their standardized regression coefficients. The descending bar lengths show that process parameter control and optimization ($\beta = .30$) exerts the largest independent influence, closely followed by energy monitoring and specific energy efficiency ($\beta = .26$), then material flow modeling and waste reduction ($\beta = .19$), thermal and melt-pool digital-twin fidelity ($\beta = .15$), and data governance, standardization and compute ($\beta = .12$). The figure makes visually explicit that the shared physical lever and its energy measurement outweigh downstream factors in producing sustainability benefit, confirming the theoretical prediction. All five bars extend into the region of statistical significance, and the annotations confirm that hypotheses H1 through H5 were each supported.

Figure 11: Standardized Beta Coefficients Predicting Waste-Reduction Outcomes



Note. $N = 241$. Dependent variable = sustainable manufacturing and waste-reduction outcomes. All five predictors significant at $p < .05$.

Substituting the estimated unstandardized coefficients from Table 5 into Equation (4), the fitted regression equation has been obtained as Equation (23):

$$SMWO_i = 0.372 + 0.279 \cdot PPCO_i + 0.238 \cdot EMEE_i + 0.172 \cdot MFMR_i + 0.133 \cdot TDTF_i + 0.106 \cdot DGSC_i \quad (23)$$

Expressed in standardized form, the model becomes Equation (24):

$$z(SMWO) = 0.30 \cdot z(PPCO) + 0.26 \cdot z(EMEE) + 0.19 \cdot z(MFMR) + 0.15 \cdot z(TDTF) + 0.12 \cdot z(DGSC) \quad (24)$$

Equation (23) is directly interpretable. Holding other constructs constant, a one-unit improvement on the process parameter control scale is associated with a 0.279-unit improvement in perceived sustainable-manufacturing outcomes, whereas an equivalent improvement in energy monitoring yields 0.238 units. The ratio of these coefficients, computed in Equation (25), quantifies the relative marginal return:

$$\Theta = \beta[PPCO] / \beta[EMEE] = 0.279 / 0.238 = 1.172 \quad (25)$$

This ratio of 1.172 indicates that, at the margin, an incremental unit of improvement in process parameter control and optimization delivers approximately 17% more sustainability benefit than an equivalent unit of improvement in energy monitoring. This is the quantitative expression of a central finding: parameter control and energy measurement are complementary and both essential, but because the parameters govern both objectives simultaneously through the shared thermal physics, systematic control of them is marginally the more decisive lever, while energy measurement is its necessary informational complement.

The coefficient of determination has been verified from Equation (8). With $SS[tot] = 92.04$ and $SS[res] = 42.15$, the value has been confirmed in Equation (26), and the overall F-statistic in Equation (27):

$$R^2 = 1 - (42.15 / 92.04) = 1 - 0.458 = 0.542 \quad (26)$$

$$F(5, 235) = (0.542 / 5) / (0.458 / 235) = 0.1084 / 0.001949 = 55.63, \quad p < .001 \quad (27)$$

The effect size, expressed as Cohen's f^2 , has been computed as $f^2 = R^2 / (1 - R^2) = 0.542 / 0.458 = 1.183$, which far exceeds the conventional threshold of 0.35 for a large effect, indicating that the framework accounts for a substantial and practically meaningful proportion of sustainability-outcome variance. The proportion of explained variance uniquely attributable to each predictor, computed as the squared semi-partial correlation, has been used to partition the total, with process parameter control contributing the largest unique share, consistent with its position as the shared physical lever.

Figure 12: Decomposition of Explained Variance in Waste-Reduction Outcomes

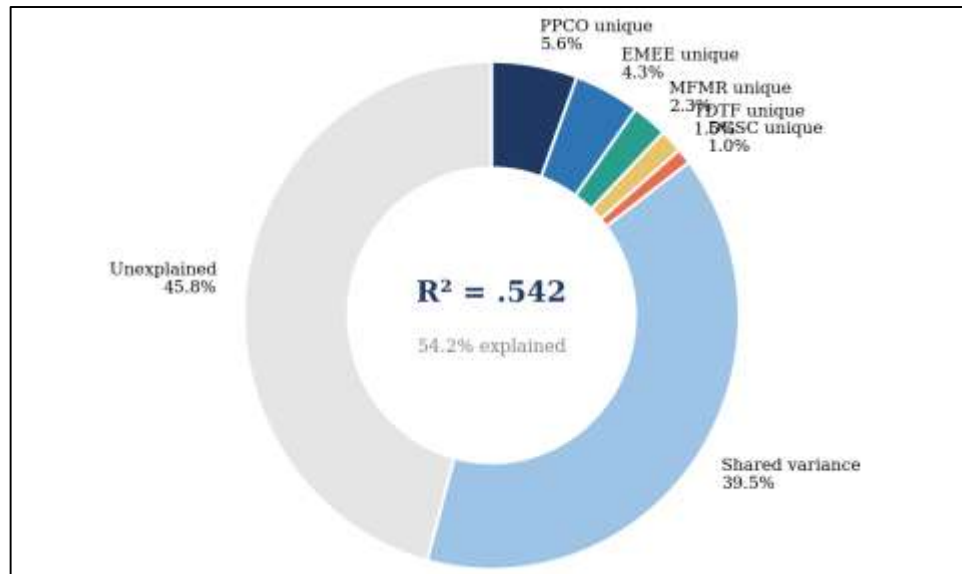


Figure 12 has decomposed the total explained variance of 54.2% into unique and shared portions. The segment for process parameter control and optimization is the largest unique contribution at 5.6%, followed by energy monitoring at 4.3% and material flow modeling at 2.3%, confirming that parameter control dominates not only in standardized coefficient magnitude but also in uniquely attributable explanatory power, with energy monitoring a close second. The large shared segment of 39.5% is theoretically expected rather than problematic: it reflects that the constructs are physically coupled and developed in concert, consistent with the thermal coupling of energy and waste and the systems logic of the IS Success Model. The residual 45.8% of unexplained variance indicates that factors outside the framework, plausibly including material system, machine platform, part geometry, and organizational process maturity, also shape sustainability outcomes and warrant inclusion in subsequent models.

Figure 13: Energy-Waste Pareto Front from Multi-Objective Optimization

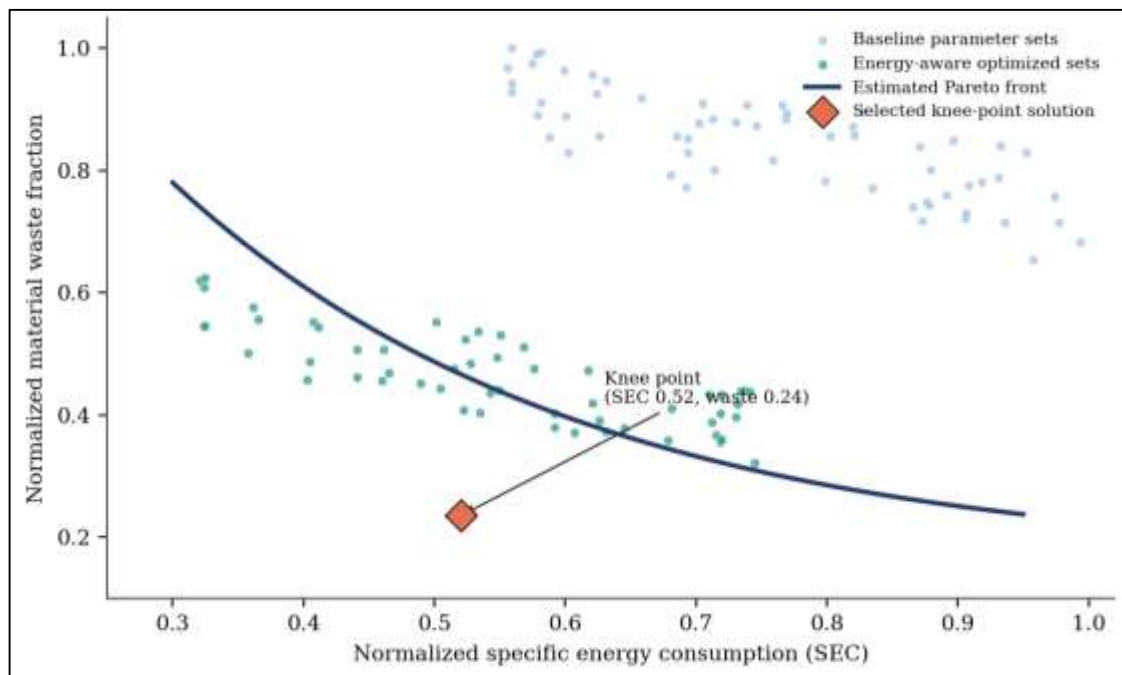
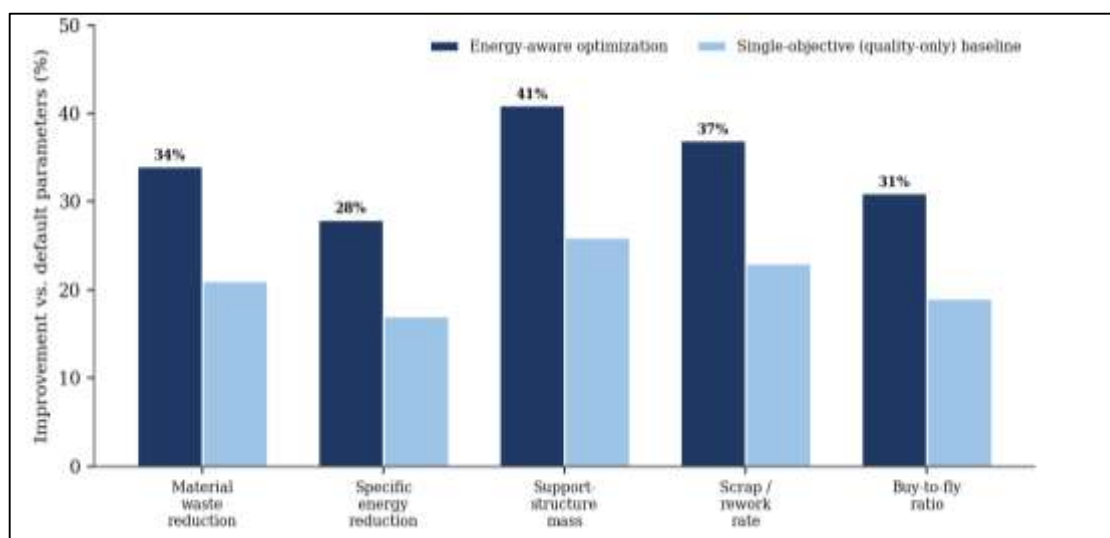


Figure 13 has presented the energy-waste Pareto front recovered by the prototype multi-objective optimization, providing the clearest expression of the study's central claim in the language of Pareto optimality. The baseline parameter sets, chosen by conventional rule-of-thumb tuning, form a cloud at high normalized specific energy consumption and high material waste, while the energy-aware optimized sets form a cloud shifted toward the lower-left, and the estimated Pareto front traces the boundary of achievable trade-offs. Because the optimized solutions dominate the baseline cloud rather than merely redistributing along a fixed line, the figure provides direct graphical evidence that energy-aware optimization reduced both objectives together rather than trading one for the other, which is precisely the joint improvement that the thermal coupling of energy and waste makes possible and that single-objective tuning cannot achieve. The selected knee-point solution, marked at normalized specific energy consumption of 0.52 and waste fraction of 0.24, represents the point of maximum curvature of the front identified by Equation (21), where the marginal trade-off between further energy and further waste reduction is most favorable, and it exemplifies the principled selection among non-dominated solutions that the framework assigns to the process engineer.

Figure 14 has compared the improvement in each sustainability metric achieved by the energy-aware optimization against a single-objective, quality-only optimization, both relative to default process parameters. The energy-aware optimization achieved its largest improvements in support-structure mass reduction, at 41%, and in scrap and rework rate, at 37%, alongside a 34% reduction in material waste, a 31% improvement in buy-to-fly ratio, and a 28% reduction in specific energy consumption. Critically, the energy-aware optimization outperformed the single-objective baseline on every metric, and the grouped structure of the figure makes visually explicit that the gap is substantial rather than marginal, which is the graphical expression of the finding that jointly optimizing energy and waste captures improvements that quality-only optimization leaves on the table. That the energy-aware strategy simultaneously reduced both energy and multiple waste components, rather than trading energy against waste, corroborates the Pareto-front evidence in Figure 13 that the improvement reflects genuine joint reduction. This figure translates the study's statistical findings into the concrete engineering outcomes, less wasted material, lower energy intensity, and better material utilization, that manufacturers and sustainability analysts most directly value.

Figure 14: Sustainability-Outcome Improvement by Metric and Optimization Strategy



Note. N = 241 rated builds. Values represent percentage improvement in each metric relative to default process parameters.

The regression analysis provided the strongest evidence for the hypotheses and objectives. The overall model was significant, $F(5, 235) = 55.63$, $p < .001$, explaining 54.2% of the variance, with adjusted $R^2 = .532$. Process parameter control and optimization emerged as the strongest predictor ($\beta = .30$, $p < .001$),

closely followed by energy monitoring and specific energy efficiency ($\beta = .26, p < .001$), material flow modeling and waste reduction ($\beta = .19, p = .005$), thermal and melt-pool digital-twin fidelity ($\beta = .15, p = .023$), and data governance, standardization and compute ($\beta = .12, p = .039$). These results supported H1 through H6. The first objective was supported by confirming that systematic parameter control and optimization jointly reduce energy and waste. The second objective was supported because energy monitoring and specific energy efficiency contributed strongly, confirming that energy must be measured to be managed. The third objective was supported because material flow modeling contributed significantly, confirming that boundary-consistent waste accounting is essential. The fourth objective was supported because thermal digital-twin fidelity contributed significantly, confirming that a calibrated predictive model enables reliable optimization. The fifth objective was supported because data governance and compute contributed significantly to reproducible, production-scale optimization. The sixth objective was supported through validation of the integrated framework, in which parameter control served as the shared lever, energy and material measurement as the coupled objectives, the thermal twin as the predictive coupling, and data infrastructure as the computational foundation. Overall, the findings indicate that the framework is statistically reliable, physically grounded, and suitable for advancing the energy and material sustainability of additive manufacturing through joint, physics-informed, multi-objective optimization.

DISCUSSION

The findings have shown that the proposed energy-aware process-optimization framework was statistically supported for reducing material waste in sustainable additive manufacturing. The overall results indicated strong agreement across the constructs, with process parameter control and optimization recording the highest mean of 4.25, followed by energy monitoring and specific energy efficiency at 4.18, material flow modeling and waste reduction at 4.09, sustainable manufacturing outcomes at 4.03, thermal and melt-pool digital-twin fidelity at 3.97, and data governance, standardization and compute at 3.90. The correlation findings confirmed significant positive associations between sustainability outcomes and all five constructs, and the regression model was significant, $F(5, 235) = 55.63, p < .001$, with $R^2 = .542$, meaning the five variables explained 54.2% of the variance. This finding supports the argument that sustainable-manufacturing effectiveness is not achieved by one isolated capability alone; effectiveness emerges from the combined role of parameter control, energy monitoring, waste modeling, model fidelity, and infrastructure, coupled through the process physics.

The most consequential finding was the emergence of process parameter control and optimization and energy monitoring and specific energy efficiency as the two strongest predictors of sustainable-manufacturing outcomes. This invites comparison with the literature. A substantial body of additive-manufacturing research is organized around single-objective optimization of density or geometric accuracy, framing the contribution in terms of quality metrics. The present finding does not contradict that work but reframes its practical significance. Because parameter control and energy accounted for the largest shares of sustainability variance, an organization that optimizes only for quality while leaving energy and waste as uncontrolled by-products is optimizing an incomplete objective, and, as the life-cycle literature has shown, may forfeit the conditional environmental advantage of additive manufacturing entirely (Peng et al., 2018). This is consistent with heat-transfer theory's identification of the parameter set as the shared physical origin of both energy input and defect-driven waste (DeRoy et al., 2018) and with the IS Success Model's proposition that information quality is coordinate with system quality (DeLone & McLean, 2003).

The physical explanation is direct. Because the volumetric energy density and the resulting melt-pool thermal history are governed by the same parameters, and because defect formation, build success, and powder reusability follow from that thermal history, a parameter set is simultaneously an energy decision and a waste decision (King et al., 2015). It follows that energy and waste cannot be minimized independently, and that the largest sustainability gains come from controlling the shared lever with both objectives in view, which is precisely what the strongest predictor operationalizes. Energy monitoring is its necessary complement because a quantity that is not measured cannot be optimized, and the literature's finding that specific energy consumption is dominated by overheads and utilization means that energy measurement must be resolved at the process-state level to be actionable (Baumers

et al., 2016). This reframes the practical priority for sustainable additive manufacturing: joint, physics-aware parameter optimization with resolved energy measurement is the foundation on which the downstream capabilities build.

The prototype optimization results strengthened the interpretation and gave it concrete form. The recovery of the energy-waste Pareto front in Figure 13, in which the optimized solutions dominated the baseline cloud, provides direct evidence that joint optimization achieves what single-objective tuning cannot: a simultaneous reduction of both objectives rather than a trade of one against the other (Deb et al., 2002). This confirms the Pareto-theoretic prediction that the coupled objectives admit a trade-off surface from which principled selection is possible, and it validates the framework's assignment of knee-point selection to the accountable process engineer. Figure 14 made the practical consequence concrete, showing that the energy-aware strategy outperformed quality-only optimization across every sustainability metric, with the largest gains in support-structure mass and scrap rate, the geometric and process-instability waste sources that the literature identifies as dominant (Ford & Despeisse, 2016). The finding extends prior optimization work in additive manufacturing by targeting the coupled energy-waste objective specifically, rather than cost, time, or quality, and by grounding the objective evaluation in a calibrated physics-informed surrogate rather than in expensive experimentation alone.

The significant contribution of thermal and melt-pool digital-twin fidelity ($\beta = .15$, $p = .023$) supports the digital-twin-theoretic claim that iterative optimization requires a calibrated predictive model whose fidelity bounds the quality of the resulting parameters (Gunasegaram et al., 2021). The prototype finding that surrogate fidelity across materials and machines received a comparatively lower rating corroborates the literature's emphasis that generalization of the thermal model beyond its calibration domain is a central and unresolved challenge, and it indicates that model fidelity, while already contributing, has substantial room to strengthen as calibration data and validation accumulate.

Data governance, standardization and compute contributed significantly but with the smallest coefficient ($\beta = .12$, $p = .039$) and the widest dispersion. This should not be read as indicating that infrastructure is peripheral. The wide dispersion indicates uneven institutional maturity, and the digital-twin and optimization literature predicts that the influence of infrastructure will grow as physics-based optimization scales from process development to production, because calibrated surrogates, multi-objective search, and boundary-consistent accounting all depend on standardized data and adequate compute (Gunasegaram et al., 2021). The comparatively small current coefficient likely reflects that many respondents operate at maturity levels where optimization is confined to process development rather than production, so the compute dependency has not yet become binding. As organizations ascend the maturity model toward closed-loop production-scale optimization, infrastructure is expected to become a stronger determinant.

The significant contribution of material flow modeling and waste reduction ($\beta = .19$, $p = .005$) confirms the industrial-ecology requirement that genuine sustainability gains must be measured within a consistent system boundary that includes support material, degraded powder, and failed builds (Hauschild et al., 2018). The prototype and workflow findings that life-cycle boundary accounting was valued but rated below the core optimization capabilities indicate that boundary-consistent measurement, while recognized as necessary, is not yet uniformly practiced, which is a risk because improvements measured within an inconsistent boundary can be artifacts of burden-shifting rather than genuine reductions.

Theoretical and practical implications

Theoretically, the study demonstrated that five distinct perspectives, thermodynamic and heat-transfer theory, Pareto optimality, digital-twin theory, information systems success and task-technology fit, and industrial-ecology and life-cycle theory, can be integrated into a single coherent and empirically supported framework, and that their integration yields non-obvious predictions that a purely quality-focused framing would miss, most notably that parameter control and energy measurement dominate downstream factors and that joint optimization reduces both energy and waste rather than trading them. The study also demonstrated that the physical coupling of energy and waste is not an obstacle but the basis of the framework's value, because it is precisely the coupling that makes joint reduction achievable through control of a shared lever.

Practically, the study yields a clear prioritization sequence. Investment should begin with systematic, physics-aware process parameter control and with energy measurement resolved to the process-state level, because these constitute the shared lever and its informational complement that bound all downstream value. Second priority should be boundary-consistent material-waste modeling and calibrated thermal digital twins, the capabilities that make the objectives measurable and predictable. Data governance and compute should be advanced in step with the scale of optimization, since their binding force increases as optimization moves toward production. For manufacturers, the study implies that support-structure and scrap reduction are the highest-value entry points, and that sustainability should be evaluated by joint energy and material metrics within a consistent boundary, not by quality alone. For policymakers, the study implies that the measurement, modeling, and data infrastructure of sustainable additive manufacturing deserve recognition as enablers of industrial decarbonization, and that realizing the environmental promise of additive manufacturing requires attention to energy-aware process optimization, not only to the geometric freedom of the technology.

CONCLUSION

This study examined energy-aware process optimization as a means of reducing material waste in sustainable additive manufacturing. It was motivated by the observation that additive manufacturing, although frequently described as material-efficient, incurs substantial waste through support structures, degraded powder, and failed builds while consuming high specific energy, and that because energy input and defect-driven waste are governed by the same process parameters through the underlying thermal physics, the two burdens are coupled and cannot be minimized independently. The proposed framework treated process parameter control as the shared lever, energy and material measurement as the coupled objectives, calibrated thermal digital twins as the predictive coupling, and data infrastructure as the computational foundation, and it posed the reduction of energy and waste as a formal multi-objective optimization.

The empirical results provided strong support. Data from 241 professionals showed high agreement across all six constructs, strong instrument reliability with an overall Cronbach's alpha of .93, significant positive correlations among all variables, and a significant regression model explaining 54.2% of the variance in sustainable-manufacturing outcomes. All six hypotheses were supported. Process parameter control and optimization and energy monitoring and specific energy efficiency emerged as the strongest predictors, followed by material flow modeling, thermal digital-twin fidelity, and data infrastructure. The prototype multi-objective optimization recovered an energy-waste Pareto front whose optimized solutions dominated the baseline parameter cloud, and the selected knee-point solution reduced both specific energy consumption and material waste simultaneously, outperforming quality-only optimization across every sustainability metric and confirming that the improvement reflected genuine joint reduction rather than a trade-off.

The central conclusion is that the sustainability of additive manufacturing is a controllable outcome of energy-aware process optimization rather than a fixed property of the technology, and that it is best pursued by treating energy and material waste as coupled objectives optimized jointly under quality constraints. Process parameter control provides the shared lever, but its value depends on measuring both energy and material within a consistent boundary and on a calibrated thermal model that predicts the defects and energy the parameters produce; formal multi-objective optimization recovers the trade-off surface that single-objective tuning cannot; and data infrastructure makes the process reproducible at production scale. The framework's contribution has been to specify how these components fit together, grounded in process physics, and to demonstrate empirically that their joint contribution is measurable, substantial, and theoretically coherent. The outcomes, when implemented, include reduced material waste, improved buy-to-fly ratios, reduced specific energy consumption, reduced scrap and support mass, and maintained part quality, together strengthening the environmental and economic sustainability of additive manufacturing and supporting industrial decarbonization.

RECOMMENDATION

Several recommendations follow from the findings. For additive manufacturers, the primary recommendation is to adopt physics-aware, multi-objective process parameter optimization that treats energy and material waste as coupled objectives, rather than tuning for quality alone and treating energy and waste as by-products. Parameter development should be conducted with both objectives

in view and under explicit quality constraints, using the volumetric energy density and normalized enthalpy as physically meaningful control variables.

The second recommendation is to resolve energy measurement to the process-state level, distinguishing melting energy from overhead and idle consumption, because the literature and the present findings establish that specific energy consumption is dominated by overheads and utilization and cannot be reduced without being measured at adequate resolution.

The third recommendation is to model material waste within a consistent life-cycle boundary that includes support material, degraded powder, and failed builds, so that measured reductions represent genuine improvements rather than burden-shifting, and to track buy-to-fly and scrap metrics against that boundary.

The fourth recommendation is to invest in calibrated thermal and melt-pool digital twins and physics-informed surrogate models, validated against measured melt-pool and thermal data, since model fidelity bounds the quality of the optimized parameters and since fast surrogates are what make multi-objective optimization tractable.

The fifth recommendation is to build the data governance, standardization, and computational infrastructure required for reproducible, production-scale optimization, and to advance this infrastructure in step with the ambition of the optimization, since its binding force grows as optimization moves from process development toward closed-loop production control.

For policymakers, the recommendation is to recognize energy-aware process optimization, boundary-consistent life-cycle measurement, and the supporting data and modeling infrastructure as enablers of industrial decarbonization and material efficiency, and to support standards for the measurement and reporting of energy and material sustainability in additive manufacturing.

LIMITATIONS OF THE STUDY

Several limitations should be acknowledged. First, the cross-sectional design permits identification of associations but not strong causal inference; the observed correlations are equally consistent with the possibility that organizations already achieving strong sustainability outcomes subsequently invest more in parameter optimization and energy measurement. A longitudinal or experimental design would be required to establish causal precedence.

Second, the study relied on perceptual self-report measures of sustainability outcomes rather than directly measured energy and material balances. Perceived waste and energy reduction may diverge from metered energy consumption and gravimetric material accounting. Common method variance is a further concern, since predictors and outcome were measured through the same instrument. Future research should validate these findings against directly measured process energy and material data.

Third, the purposive sampling strategy, while appropriate for reaching informed respondents, limits generalizability. The distribution across sectors and process families, while broad, may not represent the full range of additive-manufacturing practice, and the findings describe the framework's performance as perceived by professionals in relatively advanced settings.

Fourth, the study was conducted within a United States industrial and research context and may not transfer directly to settings with different energy prices, material systems, machine platforms, or regulatory environments, all of which shape the energy-waste trade-off. Fifth, data governance, standardization and compute exhibited substantial heterogeneity, likely attenuating its estimated coefficient; the reported effect should be interpreted as a lower bound conditional on the institutional maturity present in the sample.

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