



Physics-Informed Machine Learning for Predicting Thermal Distortion in Metal Additive Manufacturing

Debasish Adhikary¹

[1]. M. E. of Mechanical Engineering, Lamar University, Beaumont, Texas;
Email: debasish06me@gmail.com

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Abstract

Thermal distortion remains a critical challenge in metal additive manufacturing because repeated localized heating, rapid cooling, thermal expansion, plastic deformation, and residual-stress accumulation can produce warping, dimensional inaccuracies, component rejection, and costly post-processing. This study aimed to develop and quantitatively evaluate an integrated physics-informed machine-learning framework for improving thermal-distortion prediction across metal additive-manufacturing enterprise and research cases. A quantitative, cross-sectional, multiple-case-based design was employed using a structured five-point Likert-scale questionnaire. The cases included industrial manufacturing organizations, universities, research institutions, engineering laboratories, technical centers, and additive-manufacturing technology or software providers working with laser powder bed fusion, directed energy deposition, wire arc additive manufacturing, electron-beam processes, thermal simulation, process monitoring, and dimensional-quality evaluation. Of 350 questionnaires distributed, 318 were returned and 300 valid responses were retained, producing an 85.71 percent valid response rate. The key variables were Physics-Law Integration, Thermal-Process Data Quality and Integration, Thermomechanical Coupling Representation, Model Validation and Generalizability, Computational Efficiency and Real-Time Capability, and Thermal Distortion Prediction Effectiveness. Data were analyzed using descriptive statistics, Cronbach's alpha, exploratory factor analysis, Pearson correlation, multiple regression, analysis of variance, and regression diagnostics in SPSS. The instrument demonstrated strong reliability, with construct alpha coefficients ranging from .83 to .90 and an overall alpha of .92. The KMO value was .913, Bartlett's test was significant, $\chi^2(435) = 4,286.37$, $p < .001$, and the six-factor structure explained 69.80 percent of total variance. Thermal-Process Data Quality and Integration achieved the highest mean of 4.14, while Thermal Distortion Prediction Effectiveness recorded 4.09. The five predictors jointly explained 66.60 percent of the variance in prediction effectiveness, $R^2 = .666$, adjusted $R^2 = .660$, $F(5, 294) = 117.25$, $p < .001$. Thermomechanical Coupling Representation was the strongest predictor, $\beta = .30$, followed by data quality, $\beta = .26$, physics-law integration, $\beta = .21$, validation and generalizability, $\beta = .17$, and computational capability, $\beta = .11$. The findings imply that reliable distortion prediction requires coordinated physical constraints, integrated process data, coupled thermal-mechanical modeling, rigorous validation, and efficient computation rather than reliance on isolated algorithms.

KEYWORDS

Physics-Informed Machine Learning; Thermal Distortion Prediction; Metal Additive Manufacturing; Thermomechanical Coupling; Thermal-Process Data Quality

INTRODUCTION

Additive manufacturing refers to a group of advanced manufacturing processes in which three-dimensional objects are produced directly from digital models through the sequential addition of material in layers. In contrast to conventional subtractive manufacturing, which creates a component by removing material from a larger workpiece, additive manufacturing deposits material only in the locations required to construct a predetermined geometry. Metal additive manufacturing applies this layer-by-layer production principle to metallic powder, wire, or sheet feedstocks through processes such as laser powder bed fusion, electron-beam powder bed fusion, directed energy deposition, and wire arc additive manufacturing. These processes have achieved international significance because they support the production of geometrically complex, lightweight, customized, and topology-optimized components that may be difficult or economically inefficient to manufacture through conventional casting, forging, machining, or joining. Metal additive manufacturing has been applied in internationally important sectors such as aerospace, automotive production, biomedical engineering, energy generation, marine technology, defense, industrial tooling, and high-value component repair. Its capacity to manufacture near-net-shape components, reduce raw-material waste, consolidate assemblies, and repair expensive metallic parts has established its position within digitally integrated manufacturing environments. Thermal distortion, which represents the central manufacturing phenomenon examined in this research, can be defined as an unintended alteration in the shape, dimensions, alignment, or geometric accuracy of a metallic component resulting from nonuniform heating, thermal expansion, cooling, contraction, plastic deformation, and residual-stress accumulation. Metal additive manufacturing processes repeatedly expose highly localized regions of a component to concentrated thermal energy, creating severe temperature differences among molten material, recently solidified tracks, previously deposited layers, and surrounding cooler regions. These uneven thermal conditions generate constrained expansion and contraction that can produce bending, warping, curling, cracking, delamination, and dimensional deviation. Residual stresses generated during selective laser sintering and selective laser melting have been shown to influence deformation and final structural quality substantially (Mercelis & Kruth, 2006). Finite-element analysis has also demonstrated that the temperature distribution within a metallic powder layer directly affects thermal-stress development and post-solidification displacement (Patil & Yadava, 2007). Investigations of selective laser melting have further connected thermal loading and residual stress with component-scale deformation (Zaeh & Branner, 2010). Physics-informed machine learning refers to a computational approach in which machine-learning models incorporate established scientific knowledge, including governing equations, conservation laws, initial conditions, boundary conditions, constitutive relationships, and material properties, during training and prediction. This hybrid approach is particularly relevant to metal additive manufacturing because it combines the computational speed and pattern-recognition ability of machine learning with the physical consistency required to represent heat transfer, stress formation, and thermally induced deformation.

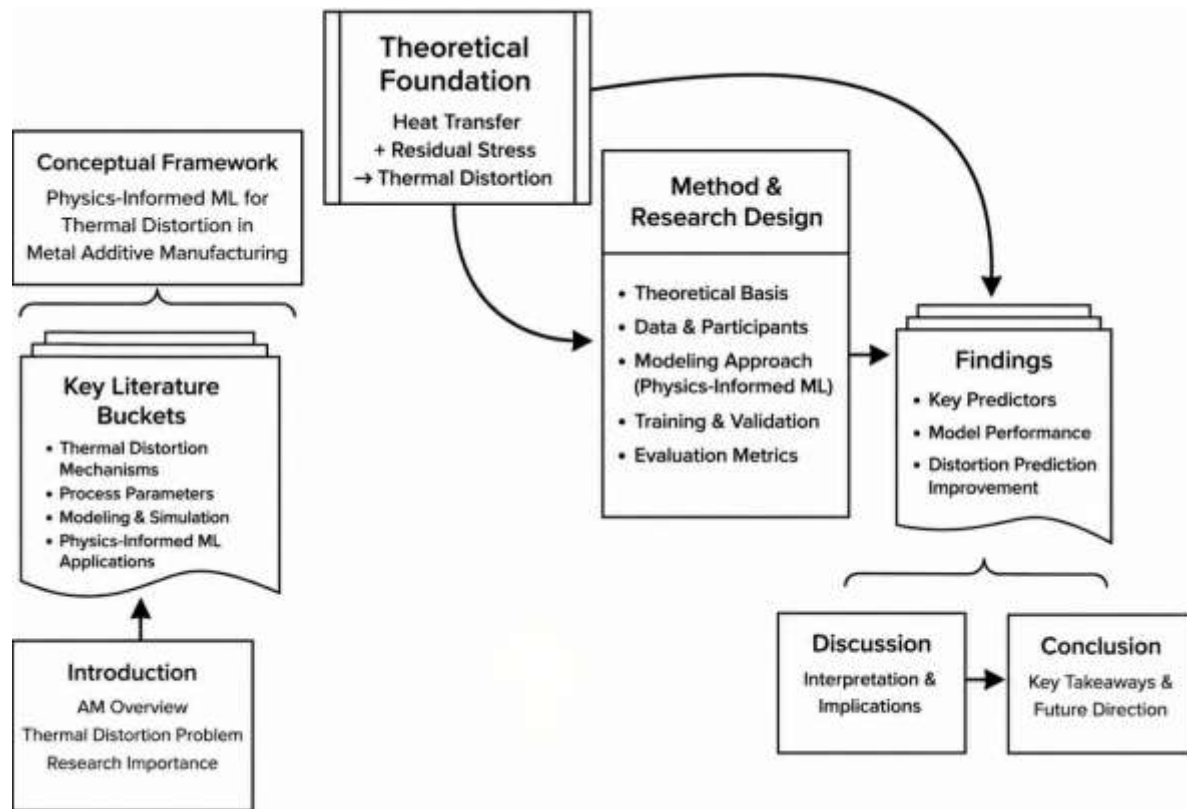
The formation of thermal distortion in metal additive manufacturing originates from the highly localized, transient, and repetitive application of heat. During laser-based, electron-beam, or arc-based deposition, a concentrated heat source creates a molten region that moves across the substrate or previously deposited material. Heat is subsequently transferred into adjacent material, earlier layers, support structures, the build plate, surrounding powder, and the external environment. Every deposited track and layer introduces another heating and cooling cycle, while nearby regions may undergo repeated reheating before the entire component reaches its final thermal state. The resulting thermal history is controlled by multiple interrelated variables, including laser or arc power, travel speed, scanning speed, hatch spacing, layer thickness, heat-source distribution, scan pattern, deposition sequence, interlayer dwell time, material conductivity, specific heat, emissivity, geometry, support configuration, and environmental boundary conditions. Nonuniform temperature distributions produce differential thermal expansion, while mechanical restraint from cooler material, the substrate, or support structures prevents free expansion and contraction. This constrained behavior generates thermal strain, elastic strain, plastic deformation, and residual stress that can remain locked inside the component after cooling. When the part is separated from the build plate or its supports are removed, the redistribution of accumulated residual stress may generate additional deformation. Accurate

directed-energy-deposition simulation has been shown to require realistic representation of surface heat losses and thermomechanical boundary conditions (Heigel et al., 2015). Interlayer dwell time has also been found to change distortion and residual-stress development in titanium and nickel alloys because the cooling period between layers alters heat accumulation and stress relaxation (Denlinger et al., 2015). A multiscale modeling approach has been used to reduce computational effort while estimating part-level deformation in selective laser melting (Li et al., 2016). In situ experimental methods have also enabled simultaneous measurement of temperature and distortion during laser powder bed fusion, allowing thermal predictions to be related more directly to observed geometric change (Dunbar et al., 2016). Melt-pool-scale research has demonstrated that fluid motion, vaporization, recoil pressure, spatter, and denudation influence local thermal behavior and establish the conditions inherited by larger-scale stress and deformation models (Khairallah et al., 2016). Thermally induced distortion has also been connected to spatially variable heating and cooling through strain-based analytical and numerical modeling (Mukherjee et al., 2017). Component-scale thermomechanical models have been experimentally validated for laser powder bed fusion, confirming that accurate distortion prediction requires close coordination between thermal calculations, mechanical response, and physical measurement (Denlinger et al., 2017). Distortion-prediction and compensation methods have further shown that the final component shape depends on the interaction among heat input, deposition sequence, geometry, constraint, and residual-stress release (Afazov et al., 2017).

Physics-based numerical modeling has traditionally served as the primary approach for representing the relationship among process parameters, thermal history, residual stress, and deformation in metal additive manufacturing. Thermal models generally solve transient heat-conduction equations while incorporating moving heat sources, latent heat, convection, radiation, material activation, and temperature-dependent thermophysical properties. The calculated temperature field is then transferred to a mechanical model that estimates thermal strain, elastic strain, plastic deformation, residual-stress accumulation, and displacement. Fully coupled thermomechanical simulations can provide detailed information about temperature, strain, stress, and deformation throughout the build. Their application is constrained by the substantial difference between the spatial and temporal scales of a melt pool and those of an industrial component. A melt pool may occupy a region measured in micrometers or millimeters, while the complete part may contain thousands of scan tracks and hundreds or thousands of deposited layers. Accurately following every heat-source movement, material-activation event, phase-dependent property, nonlinear constitutive response, and mechanical interaction requires fine numerical meshes, short time steps, repeated iterations, and extensive computational resources. Researchers have therefore developed layer-aggregation techniques, inherent-strain approaches, reduced-order formulations, multiscale methods, thermal circuit networks, activation strategies, and calibrated part-scale models to improve computational efficiency. A thermal circuit network was developed to provide rapid thermal and distortion prediction for metal powder bed fusion while reducing the computational burden of complete finite-element analysis (Peng et al., 2018). A thermomechanical model for laser powder bed fusion of Ti-6Al-4V was evaluated against experimentally measured residual stress, demonstrating the importance of physical calibration and validation (Ganeriwala et al., 2019). Experimental validation has also been conducted for part-scale thermomechanical models intended to estimate process-induced temperature, stress, and deformation (Gouge et al., 2019). An immersed thermomechanical framework was assessed for predicting post-build deflection and component-scale deformation in laser powder bed fusion (Carraturo et al., 2020). A sequential flash-heating approach was similarly evaluated through experimental measurements to determine whether simplified layerwise thermal loading could reproduce part distortion accurately (M. Bayat et al., 2020). Multi-laser scanning strategies have also been shown to influence temperature distribution, residual stress, and final deformation because the sequence and interaction of multiple heat sources modify thermal accumulation throughout the component (Zhang et al., 2020). These investigations have strengthened the physical foundations of thermal-distortion prediction, while also showing that simulation accuracy depends on assumptions regarding heat-source calibration, boundary conditions, material properties, mesh resolution, mechanical constitutive behavior, and experimental comparison. High-fidelity models can provide detailed predictions within a carefully

calibrated setting, but their computational requirements can limit repeated use during process-parameter selection, manufacturing planning, and rapid optimization. Simplified numerical models can reduce execution time, although excessive simplification can remove localized thermal information that is necessary for accurate stress and displacement estimation. The requirement to preserve physical relationships while decreasing computational cost provides the technical basis for integrating machine learning with thermomechanical modeling.

Figure 1: Research Process Framework for Thermal Distortion Prediction Using Physics-Informed Machine Learning



Machine learning has increasingly been applied to metal additive manufacturing as a method for identifying nonlinear relationships among process inputs, thermal histories, geometric characteristics, material behavior, and manufacturing outcomes. Machine-learning models can be trained using experimental measurements, process-monitoring signals, numerical simulation results, machine-control records, geometric descriptors, or combinations of these sources. In thermal prediction, input variables may include laser power, arc current, wire-feed rate, scanning speed, hatch spacing, layer number, deposition time, scan direction, spatial coordinates, material properties, boundary conditions, and previous temperature states. Predicted outputs may include peak temperature, cooling rate, complete thermal history, melt-pool dimensions, residual stress, bead geometry, directional displacement, or final distortion. Recurrent neural networks have been used to predict high-dimensional thermal histories in directed-energy-deposition processes by learning sequential and time-dependent relationships associated with layerwise fabrication (Mozaffar et al., 2018). Data-driven surrogate modeling has also been used to convert geometry and heat-source information into rapid thermal-history estimates, reducing the need for repeated full-scale numerical simulations (Roy & Wodo, 2020). Artificial neural networks have been applied to predict the geometry and distortion of multilayer components produced through wire arc additive manufacturing (Wacker et al., 2021). Physics-based features have also been incorporated into machine-learning models to improve thermal-history prediction across changing additive-manufacturing geometries (Ness et al., 2022). Numerical simulation and feedforward neural networks have been combined to accelerate the prediction of thermal histories in wire arc additive manufacturing (Le et al., 2023). An artificial-intelligence

framework has been applied to high-fidelity heat-transfer and thermal-distortion forecasting in multi-laser powder bed fusion, with learned predictions showing close correspondence with numerical outputs (Ball & Basak, 2023). Physics-informed neural networks trained with randomly synthesized data have also been investigated as a method for accelerating additive-manufacturing thermal simulations (Chen, Pierce, et al., 2024). The transferability of machine-learning temperature predictions has been examined across different wire arc geometries and process conditions, revealing that prediction performance can change when the geometry or scanning parameters differ from those represented during training (Fagersand et al., 2024). Fourier neural operators have also been applied to learn localized temperature evolution across geometrically variable additive-manufacturing domains (Chen, Xu, et al., 2024). These studies demonstrate that machine-learning models can generate rapid predictions after training. Their reliability remains dependent on the quality, coverage, and physical relevance of the training data. A model trained using a narrow range of materials, geometries, heat-source parameters, or machine configurations may accurately reproduce cases located inside its training domain while generating uncertain predictions under unfamiliar conditions. Sensor noise, incomplete measurements, inconsistent simulation assumptions, emissivity uncertainty, and inadequate representation of heat-affected regions may also reduce predictive accuracy. Purely data-driven models can therefore reproduce statistical associations without necessarily satisfying conservation laws, boundary conditions, or thermomechanical relationships.

Physics-informed machine learning provides a structured approach for integrating scientific knowledge with statistical learning so that model predictions are influenced by both observed data and governing physical relationships. In a conventional supervised-learning model, the algorithm is generally trained by minimizing the difference between predicted and observed outputs. In a physics-informed system, the training objective may additionally penalize violations of partial differential equations, initial conditions, boundary conditions, conservation principles, constitutive equations, or other physically meaningful restrictions. Physics-informed neural networks established a general framework for solving forward and inverse problems governed by nonlinear partial differential equations through automatic differentiation and equation-based loss functions (Raissi et al., 2019). Physics-constrained deep learning has also demonstrated that scientific restrictions can support high-dimensional surrogate modeling and uncertainty quantification when labeled data are limited or unavailable (Zhu et al., 2019). In solid mechanics, physics-informed deep learning has been extended to inversion and surrogate modeling through the incorporation of momentum balance, elasticity, and elastoplastic constitutive relationships (Haghighat et al., 2021). These foundations are directly relevant to thermal-distortion prediction because metal additive manufacturing combines transient heat transfer, thermal expansion, mechanical equilibrium, material nonlinearity, plastic deformation, and continuously changing structural constraints. Physics-informed neural networks have been applied to predict temperature and melt-pool fluid dynamics in metal additive manufacturing by incorporating the conservation of mass, momentum, and energy into the learning process (Zhu et al., 2021). Hybrid thermal models have combined incomplete infrared measurements with heat-transfer equations to reconstruct full temperature fields and identify unknown process or material parameters (Liao et al., 2023). A physics-informed model has also been used to predict temperature and melt-pool dimensions using limited labeled data, indicating that governing knowledge can supplement incomplete experimental datasets (Jiang et al., 2024). Physics-informed online learning has further been applied to temperature prediction during metal additive manufacturing, allowing the learning system to integrate new thermal information while maintaining physical constraints (Sajadi et al., 2024). Physical knowledge may enter a model through equation residuals, engineered physics-based features, constrained outputs, synthetic data generated by validated simulations, hybrid loss functions, reduced-order representations, or interactions between mechanistic and statistical submodels. The degree of physics integration can therefore vary substantially among models. One system may be classified as physics informed because it includes a limited heat-transfer relationship, while another may incorporate energy conservation, phase change, material properties, heat-source behavior, thermal expansion, mechanical equilibrium, and plastic constitutive behavior. For thermal-distortion prediction, representing the temperature field alone is insufficient. The model must preserve a physically meaningful relationship among heat input, temperature evolution, thermal strain, residual

stress, stress redistribution, and final displacement. Physics-law integration and thermomechanical coupling representation consequently constitute distinct but closely connected capabilities in the evaluation of PIML-based distortion prediction.

The effectiveness of a physics-informed thermal-distortion model depends not only on its mathematical architecture but also on the quality of the thermal and mechanical information used for training, calibration, and validation. Data in metal additive manufacturing may be collected through infrared cameras, thermocouples, pyrometers, photodiodes, acoustic systems, melt-pool imaging devices, machine-control records, finite-element simulations, diffraction-based residual-stress measurements, coordinate-measuring machines, digital image correlation, or three-dimensional scanning. These data sources vary in spatial resolution, temporal frequency, physical meaning, synchronization, uncertainty, accessibility, and measurement coverage. In situ measurement research has demonstrated the importance of recording temperature and distortion simultaneously so that predicted thermal histories can be associated directly with observed deformation (Dunbar et al., 2016). Experimental assessment of thermomechanical models has shown that numerical residual-stress predictions should be compared with physical measurements rather than assessed only through internal computational consistency (Ganeriwala et al., 2019). Part-scale validation has also confirmed the importance of comparing modeled thermal and mechanical fields with experimentally observed component behavior (Gouge et al., 2019). Immersed thermomechanical modeling has further demonstrated the need to validate predicted post-build deflection against measured geometry (Carraturo et al., 2020). Sequential flash-heating simulations have similarly been compared with experimental distortion measurements to evaluate whether simplified thermal representations preserve the essential deformation response (M. Bayat et al., 2020). Thermal-process data quality may therefore be understood through accuracy, completeness, consistency, resolution, synchronization, representativeness, and traceability. Data integration is equally important because thermal distortion originates from relationships among process parameters, temperature fields, material properties, mechanical constraints, residual stress, and final geometry. A model trained on poorly aligned or disconnected datasets may learn incomplete relationships even when individual measurements appear accurate. Model validation and generalizability determine whether a prediction system can produce credible results outside its original training cases. Evaluation should examine peak temperatures, cooling rates, heat-affected regions, stress distributions, directional displacements, and deformation after support or substrate removal. Transferability analysis has shown that prediction performance may decline when geometry or scanning speed differs from the training configuration (Fagersand et al., 2024). Neural-operator research has also emphasized that localized temperature evolution should be evaluated instead of relying exclusively on global average-error measures (Chen, Xu, et al., 2024). Computational efficiency forms another necessary capability because a technically accurate model may remain unsuitable for repeated planning or rapid monitoring when it requires extensive processing. Rapid thermal networks have been designed to reduce calculation time while retaining essential process information (Peng et al., 2018). Data-driven surrogate models have likewise been developed to replace repeated thermal simulations with faster learned approximations (Roy & Wodo, 2020). Physics-based machine-learning features have been used to improve prediction efficiency and transferability (Ness et al., 2022). Hybrid neural and numerical models have reduced the time required for thermal-history calculation (Le et al., 2023). Synthesized training datasets have been employed to accelerate physics-informed thermal simulation (Chen, Pierce, et al., 2024). Online-learning methods have also been used to update temperature predictions efficiently during metal additive manufacturing (Sajadi et al., 2024).

Existing research has made substantial progress in modeling temperature fields, residual stresses, melt-pool behavior, thermal histories, deformation mechanisms, and part-scale distortion in metal additive manufacturing. The available evidence remains distributed across different manufacturing processes, materials, geometries, model scales, data sources, validation procedures, and prediction criteria. Many investigations have evaluated one algorithm using a single alloy, component geometry, machine configuration, heat-source arrangement, or experimental dataset. Laser powder bed fusion studies have frequently concentrated on melt-pool physics, transient temperature, residual stress, and substrate-release deformation. Directed-energy-deposition and wire arc additive-manufacturing studies have commonly focused on sequential thermal histories, deposited-wall geometry, bead

development, and layerwise distortion. Physics-informed investigations have frequently predicted temperature or melt-pool characteristics without directly examining the complete progression from thermal input to stress accumulation and final dimensional change. Research has also treated computational acceleration, transferability, data quality, physical constraints, experimental validation, and uncertainty as separate technical issues. The combined relationships among Physics-Law Integration, Thermal-Process Data Quality and Integration, Thermomechanical Coupling Representation, Model Validation and Generalizability, Computational Efficiency and Real-Time Capability, and Thermal Distortion Prediction Effectiveness have received limited empirical examination within one explanatory structure. The present research is designed as a quantitative, cross-sectional, case-study-based investigation involving professionals and technical environments associated with metal additive manufacturing, process modeling, machine learning, thermal simulation, process monitoring, or dimensional-quality evaluation. Thermal Distortion Prediction Effectiveness is defined as the perceived ability of a physics-informed machine-learning system to generate accurate, consistent, timely, physically credible, and technically useful predictions of thermally induced dimensional change. Physics-Law Integration refers to the incorporation of governing equations, conservation principles, boundary conditions, material properties, and other scientific restrictions within the learning process. Thermal-Process Data Quality and Integration represent the accuracy, completeness, synchronization, resolution, and coordinated use of experimental and simulated information. Thermomechanical Coupling Representation concerns the ability of the model to connect temperature evolution with thermal strain, plastic deformation, residual stress, and displacement. Model Validation and Generalizability refer to the extent to which predictions are confirmed against physical or numerical evidence and remain reliable across different process conditions. Computational Efficiency and Real-Time Capability describe the speed, scalability, and resource requirements of the prediction system. A structured questionnaire based on a five-point Likert scale will measure professional assessments of these constructs across selected manufacturing, laboratory, and research cases. Descriptive statistics will establish their measured levels and rankings. Pearson correlation analysis will determine the direction and strength of the relationships among the variables. Multiple regression modeling will estimate the individual and combined contributions of the five independent constructs to Thermal Distortion Prediction Effectiveness and will provide the statistical basis for testing the proposed hypotheses.

Background of the Study

Metal additive manufacturing has emerged as an advanced production approach through which metallic components are fabricated directly from three-dimensional digital models by depositing and consolidating material in successive layers. Processes such as laser powder bed fusion, directed energy deposition, electron beam powder bed fusion, and wire arc additive manufacturing have enabled manufacturers to produce geometrically complex, lightweight, customized, and high-value components for aerospace, automotive, biomedical, energy, defense, marine, and tooling applications. The layerwise nature of these processes provides considerable design flexibility, yet it also creates complicated thermal conditions that are difficult to control. During manufacturing, a highly concentrated heat source repeatedly melts and reheats localized regions while surrounding material remains comparatively cooler. This uneven heating and cooling produce steep thermal gradients, constrained expansion, plastic deformation, residual stress, and dimensional instability. As a result, components may experience warping, bending, curling, shrinkage, cracking, or other forms of thermal distortion that reduce geometric accuracy and manufacturing reliability. Conventional numerical methods, particularly finite-element thermomechanical simulation, have been widely used to estimate temperature distribution, residual stress, and deformation. These methods can provide detailed physical information, but they often require extensive computational time, complex material-property data, fine numerical meshes, and repeated model calibration. Purely data-driven machine-learning models offer faster prediction, although their performance may become unreliable when they are applied to unfamiliar materials, geometries, machines, or process conditions. Physics-informed machine learning has therefore become an important hybrid approach because it integrates governing physical principles with machine-learning algorithms. By embedding heat-transfer relationships, material behavior, initial conditions, boundary conditions, conservation principles, and

thermomechanical constraints into the learning process, physics-informed models can potentially improve physical consistency while reducing computational cost. The effectiveness of such systems, however, depends on several interconnected capabilities. These include the extent of physics-law integration, the quality and integration of thermal-process data, the representation of thermomechanical coupling, the validation and generalizability of the model, and its computational efficiency and real-time capability. The present study has been developed to examine these factors systematically within metal additive manufacturing environments and to determine how they influence the overall effectiveness of thermal-distortion prediction.

Problem Statement

Thermal distortion remains one of the most persistent technical challenges affecting the dimensional accuracy, structural reliability, and production consistency of metal additive manufacturing (Debasish, 2021; Md. Abdur & Iftekhhar, 2021). The rapid movement of concentrated heat sources creates repeated cycles of melting, solidification, reheating, and cooling, which generate complex temperature distributions across deposited tracks, layers, support structures, and substrates (Mohammad Shoriful Hossan, 2021; Muhammad Zahidul & Amena Begum, 2022). These thermal conditions lead to uneven expansion and contraction, plastic strain, residual-stress accumulation, and deformation during fabrication or after the component has been removed from the build plate. When distortion exceeds acceptable tolerances, the manufactured part may require costly post-processing, redesign, additional support structures, repeated production, or complete rejection (Md Mesbaul, 2023; Mst Shurovi, 2024). The prediction of thermal distortion is therefore essential for controlling build quality, selecting process parameters, optimizing scan strategies, and reducing manufacturing waste. Existing finite-element and physics-based thermomechanical models can represent many of the mechanisms involved in temperature and stress evolution, but their computational requirements often increase considerably with part size, geometric complexity, mesh resolution, layer count, and nonlinear material behavior (Muhammad Zahidul, 2024; Shima Ali et al., 2024). Their use for repeated parameter optimization or real-time decision support may therefore be limited. Data-driven machine-learning models can reduce prediction time, but they may depend on large and representative training datasets, and their outputs may violate physical principles when applied outside the conditions represented during training (Md Arif Uz et al., 2025; Tonay et al., 2024). Physics-informed machine learning offers a potential means of addressing these limitations by combining process data with governing thermal and mechanical knowledge. However, the presence of physical information within a model does not automatically guarantee accurate or transferable distortion prediction. Limited physical constraints, poor-quality sensor data, incomplete thermomechanical representation, weak experimental validation, low transferability, and high computational requirements can reduce model effectiveness (Md Mesbaul, 2025; Md Mostafizur, 2025). Existing research has often evaluated individual algorithms, specific materials, single geometries, isolated process conditions, or temperature prediction without examining the combined factors that influence complete thermal-distortion prediction (Md Mostafizur et al., 2025; Md Syeedur & Sharmin, 2025). There remains a lack of quantitative evidence showing how physics-law integration, thermal-process data quality, thermomechanical coupling representation, model validation and generalizability, and computational efficiency collectively and individually affect thermal-distortion prediction effectiveness across different metal additive manufacturing cases. This gap makes it difficult to identify which capabilities deserve the greatest technical and organizational attention. The present study addresses this problem by developing and testing an empirical framework that measures these factors through professional assessments and examines their relationships using descriptive statistics, correlation analysis, and multiple regression modeling.

The principal purpose of this study is to evaluate the factors that influence the effectiveness of physics-informed machine learning for predicting thermal distortion in metal additive manufacturing. The research seeks to develop a quantitative understanding of how the major technical capabilities of a physics-informed prediction system contribute to accurate, consistent, timely, physically credible, and practically useful distortion estimates. To achieve this purpose, the study will first assess the perceived levels of Physics-Law Integration, Thermal-Process Data Quality and Integration, Thermomechanical Coupling Representation, Model Validation and Generalizability, Computational Efficiency and Real-Time Capability, and Thermal Distortion Prediction Effectiveness across selected metal additive

manufacturing cases. It will then examine the direction and strength of the relationships between each independent construct and the dependent variable. The study will specifically determine whether the incorporation of governing heat-transfer and mechanical principles improves prediction effectiveness, whether accurate and synchronized thermal-process data strengthen model performance, and whether the representation of temperature, strain, residual stress, and displacement relationships contributes to more reliable distortion estimation. It will also evaluate whether model validation, explainability, robustness, and transferability across materials, geometries, processes, and machines improve confidence in predictions. Another objective is to determine whether computational speed, scalability, and real-time capability support the practical effectiveness of physics-informed models. Through multiple regression analysis, the study will estimate the individual contribution of each predictor while considering the influence of the remaining variables. This will allow the research to identify the factor that provides the strongest statistical contribution to Thermal Distortion Prediction Effectiveness. The study will also compare relevant organizational and professional characteristics, such as additive-manufacturing process type, respondent experience, model-development exposure, and organizational setting, where appropriate. The broader objective is to establish an integrated evidence-based structure that connects physical knowledge, process data, thermomechanical learning, model verification, and computational capability. By using a structured five-point Likert-scale instrument and analyzing data through descriptive, correlational, and regression techniques, the research will provide a systematic assessment of the conditions under which physics-informed machine learning is perceived to perform effectively in predicting thermal distortion within metal additive manufacturing.

Research Hypotheses

The research hypotheses have been formulated to test the proposed relationships between the five independent variables and Thermal Distortion Prediction Effectiveness. The first hypothesis, H1, states that Physics-Law Integration has a positive and statistically significant influence on Thermal Distortion Prediction Effectiveness. This hypothesis assumes that incorporating heat-conduction equations, energy-conservation principles, initial conditions, boundary conditions, temperature-dependent material properties, thermal-expansion relationships, and mechanical constraints improves the physical credibility and accuracy of model outputs. The second hypothesis, H2, states that Thermal-Process Data Quality and Integration have a positive and statistically significant influence on Thermal Distortion Prediction Effectiveness. This relationship is based on the expectation that accurate, complete, synchronized, representative, and sufficiently resolved process data allow the model to learn more reliable connections among process parameters, thermal histories, and deformation outcomes. The third hypothesis, H3, proposes that Thermomechanical Coupling Representation has a positive and statistically significant influence on Thermal Distortion Prediction Effectiveness. This hypothesis reflects the view that an effective prediction system must connect thermal history with expansion, strain, plastic deformation, residual stress, stress redistribution, and final component displacement rather than predicting temperature in isolation. The fourth hypothesis, H4, states that Model Validation and Generalizability have a positive and statistically significant influence on Thermal Distortion Prediction Effectiveness. This hypothesis assumes that models validated against experimental measurements, numerical benchmarks, multiple geometries, different materials, and varying process conditions will generate more dependable and transferable predictions. The fifth hypothesis, H5, proposes that Computational Efficiency and Real-Time Capability have a positive and statistically significant influence on Thermal Distortion Prediction Effectiveness. This relationship is based on the expectation that rapid inference, scalable computation, reduced simulation time, and timely model updating improve the usefulness of a prediction system during process planning, monitoring, and decision-making. These hypotheses will be tested through Pearson correlation analysis and multiple regression modeling. Statistical significance will be evaluated using an appropriate probability threshold, while standardized regression coefficients will be used to compare the relative contribution of the predictors. A supported hypothesis will indicate that the corresponding capability contributes meaningfully to Thermal Distortion Prediction Effectiveness within the selected study cases.

Significance of the Research

i. Significance to metal additive manufacturing organizations: The study will provide manufacturing organizations with a structured understanding of the capabilities that influence the effectiveness of

physics-informed thermal-distortion prediction. The results may help organizations determine whether greater attention should be directed toward physical-model development, sensor-data quality, thermomechanical integration, validation practices, or computational infrastructure. This evidence may support more informed decisions regarding model selection, technology investment, process planning, and distortion-control strategies.

ii. Significance to engineers and technical professionals: Additive-manufacturing engineers, thermal analysts, computational mechanics specialists, data scientists, and quality professionals may use the findings to understand how different technical components interact within a physics-informed prediction system. The study will clarify that accurate thermal prediction alone may not be sufficient when stress evolution, plastic strain, boundary conditions, and final displacement are not represented adequately. It will also emphasize the importance of validating model outputs against measurable manufacturing behavior.

iii. Significance to machine-learning developers: The research will provide machine-learning developers with empirical evidence concerning the role of governing equations, process-data quality, model transferability, and computational efficiency. The findings may assist developers in designing models that are not only statistically accurate but also physically consistent, explainable, robust, and suitable for application across varying additive-manufacturing conditions.

iv. Significance to researchers and academic institutions: The study will extend existing research by examining multiple PIML capabilities within one quantitative explanatory framework. It will offer a measurement structure that may be adapted, validated, or expanded in later studies involving experimental data, simulation outputs, digital twins, or direct algorithm comparison. Academic researchers may also use the proposed constructs and hypotheses as a basis for examining other manufacturing defects or process-performance outcomes.

v. Significance to industrial quality and process-control practices: The study will contribute to the understanding of how effective prediction systems can support dimensional-quality control, process-parameter evaluation, build preparation, and early identification of distortion risk. By identifying the strongest predictors of model effectiveness, the research may support more focused technical improvement and reduce reliance on trial-and-error manufacturing practices.

LITERATURE REVIEW

The literature review examines the theoretical, technical, and empirical foundations of physics-informed machine learning for predicting thermal distortion in metal additive manufacturing. Metal additive manufacturing is governed by complex interactions among heat-source behavior, material properties, deposition sequence, geometry, phase transformation, mechanical constraint, and repeated thermal cycling. These interactions produce temperature gradients, thermal strain, residual stress, and deformation that may reduce the dimensional accuracy of manufactured components. The prediction of thermal distortion has traditionally relied on analytical models, finite-element simulations, inherent-strain methods, reduced-order models, and experimentally calibrated thermomechanical approaches. These methods provide important physical information, yet their computational demands can limit their application to large components, repeated process optimization, and rapid manufacturing decisions. Machine-learning techniques have been introduced to learn nonlinear relationships among process variables, thermal histories, melt-pool characteristics, residual stress, and deformation. Their capacity to generate rapid predictions has made them increasingly relevant to additive-manufacturing research. However, conventional data-driven models may perform poorly when training data are incomplete, noisy, unrepresentative, or restricted to limited materials, geometries, and process conditions. Physics-informed machine learning has emerged as a hybrid modeling approach that incorporates governing equations, physical constraints, boundary conditions, material behavior, and process knowledge into statistical learning. This approach seeks to balance physical credibility with computational efficiency. The literature review therefore evaluates the physical origins of thermal distortion, the strengths and limitations of conventional thermomechanical prediction, the development of machine-learning applications in metal additive manufacturing, and the role of physics-informed learning in thermal and mechanical modeling. It also examines the major constructs selected for the present study, including Physics-Law Integration, Thermal-Process Data Quality and Integration, Thermomechanical Coupling Representation, Model Validation and Generalizability,

Computational Efficiency and Real-Time Capability, and Thermal Distortion Prediction Effectiveness. The Scientific Machine Learning Framework will be reviewed as the central theoretical foundation because it explains how scientific knowledge, computational modeling, and observational data can be combined within a unified learning structure. The review will also develop the conceptual relationships connecting the independent variables with the dependent construct and will establish the empirical basis for the proposed research hypotheses.

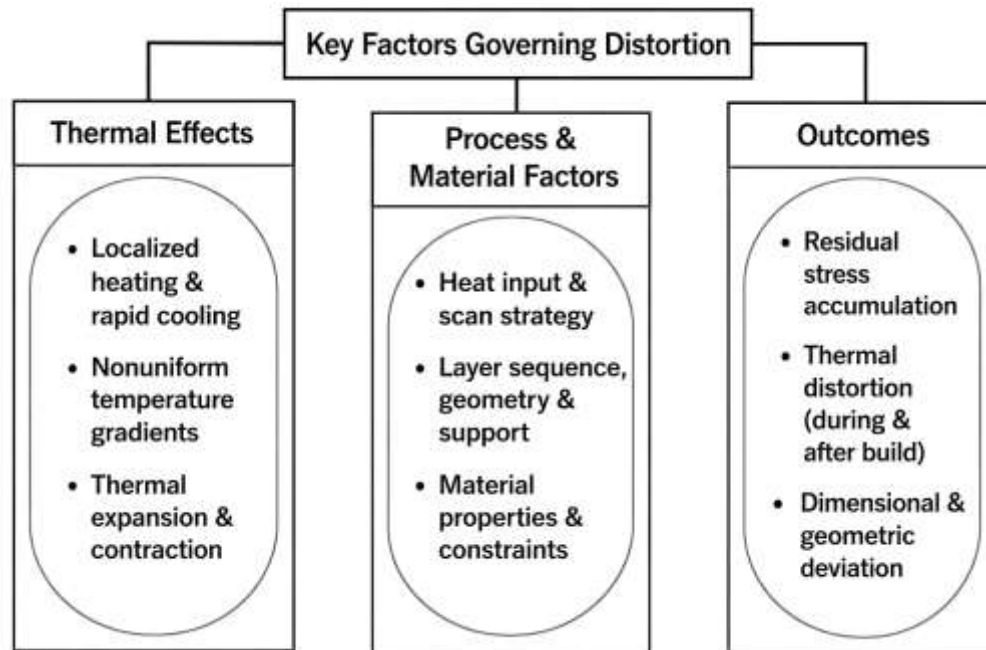
Thermal Distortion and Residual Stress in Metal Additive Manufacturing

Thermal distortion and residual stress are among the most consequential physical outcomes of metal additive manufacturing because they arise directly from the nonuniform and repeated thermal cycles used to build a component layer by layer. Thermal distortion refers to an unintended dimensional or geometric change produced when different regions of a part expand, contract, yield, and cool at unequal rates. Residual stress refers to the internal stress that remains in the material after the external heat source has moved away and the component has reached mechanical equilibrium. During powder bed fusion, directed energy deposition, and wire arc additive manufacturing, a concentrated laser, electron beam, or electric arc rapidly heats a small volume of material above its melting temperature. The molten region then solidifies while adjoining material remains cooler and mechanically constrains its contraction. Subsequent layers reheat earlier deposits and generate additional thermal cycles, causing complex interactions among elastic strain, plastic strain, phase transformation, thermal expansion, and stress redistribution. Three-dimensional thermal modeling has shown that successive layer activation produces repeated temperature peaks in previously deposited regions and gradual heat accumulation in lower layers, establishing the thermal gradients from which cyclic stress develops (Roberts et al., 2009). The magnitude and direction of the resulting stress field depend on the balance between local heating, heat conduction into the substrate, surface heat loss, scan timing, and mechanical restraint. In powder bed fusion, residual stresses may become highly anisotropic and may approach levels capable of promoting geometric distortion, cracking, delamination, or reduced fatigue resistance (Bartlett & Li, 2019). Distortion may occur during deposition as curling or bending, or it may become more visible after the supports are removed or the component is separated from the build plate. The release of constraint allows the existing stress field to redistribute, which can alter angles, flatness, wall position, and overall dimensional accuracy. The close connection between transient temperature, residual stress, and final deformation makes thermal history the essential physical link between processing conditions and component geometry.

The development of residual stress and distortion varies across metal additive manufacturing processes because heat-source intensity, deposition rate, feedstock form, layer dimensions, and thermal boundary conditions differ considerably. Wire arc additive manufacturing generally applies a relatively large heat input and deposits material at a high rate, producing broad thermal fields and substantial interaction between the deposited wall and the supporting plate. Thermomechanical analysis of large multilayer wire arc structures has shown that repeated deposition creates a characteristic stress distribution across the wall and that unclamping can redistribute this stress and generate bending deformation (Ding et al., 2011). Laser powder bed fusion employs thinner layers and a smaller moving heat source, but its rapid scanning and cooling create steep local gradients over thousands of tracks. Scan strategy therefore becomes a major factor because it controls the direction, length, sequence, and repetition of thermal loading. Thermomechanical simulation has demonstrated that changes in scan-vector length and scanning pattern modify temperature history and residual-stress development, meaning that identical energy input can generate different stress fields when the spatial sequence of exposure changes (Parry et al., 2016). Build geometry also affects thermal distortion because thin walls, overhangs, sharp transitions, unsupported regions, and large cross-sectional changes do not conduct or resist heat uniformly. Long scan paths can create directional stress accumulation, whereas rotating or segmented patterns may redistribute thermal loading but also introduce localized interactions between adjacent regions. Substrate thickness and stiffness influence the degree of mechanical restraint during fabrication, while support structures provide heat-transfer paths and prevent movement at the cost of additional stress concentration. Material properties further shape the response because thermal conductivity, elastic modulus, yield strength, coefficient of thermal expansion, heat capacity, and phase-transformation behavior vary with alloy and temperature. Consequently, thermal distortion

cannot be explained by volumetric energy density alone. A credible analysis must consider the time-dependent combination of energy delivery, geometry, thermal transport, temperature-dependent constitutive behavior, deposition sequence, and constraint.

Figure 2: Thermal Distortion Mechanism Framework for Metal Additive Manufacturing



The measurement, prediction, and control of residual stress are essential for understanding thermal distortion because the stress field cannot be evaluated reliably from final part shape alone. A component may exhibit limited visible deformation while retaining high tensile stress, or it may deform substantially after cutting because the original substrate constraint concealed the stored elastic energy (Zahidul, 2025; Kanti, 2025). Residual stress can be measured through techniques such as X-ray diffraction, neutron diffraction, the contour method, hole drilling, and layer-removal procedures, while distortion can be quantified through coordinate measurement, optical scanning, displacement sensors, and comparison between the manufactured geometry and its digital model. Each technique provides information at a different spatial depth and resolution, which makes method selection important when validating thermomechanical or machine-learning predictions. Depth-resolved X-ray diffraction measurements on selectively laser-melted AISI 316L specimens have revealed that stress varies through the surface and subsurface regions rather than remaining uniform throughout the component (Yousuf et al., 2025; Shima Ali et al., 2025; Simson et al., 2017). Such variation indicates that a single surface measurement or one global displacement value may not represent the complete thermomechanical condition of an additively manufactured part. Prediction frameworks must therefore distinguish between local thermal stress during scanning, residual stress after cooling, and deformation following support or substrate release. They should also represent the sequence through which temperature gradients create incompatible strain, plasticity locks part of that strain into the material, and constraint release converts stored stress into observable displacement. Mitigation practices include substrate preheating, optimized scan sequencing, reduced thermal gradients, modified support design, interlayer dwell control, mechanical working, stress-relief heat treatment, and geometric compensation. These practices act at different stages and do not remove the need for prediction because their effectiveness depends on material, geometry, process, and loading history. For physics-informed machine learning, residual stress and distortion provide a demanding test of model completeness. A model that predicts temperature accurately but omits mechanical equilibrium, temperature-dependent plasticity, constraint, or stress release may fail to reproduce final geometry. Thermal distortion prediction therefore requires coordinated thermal, mechanical, material, and measurement information rather than an isolated relationship between process parameters and displacement.

Conventional Physics-Based and Data-Driven Distortion Prediction Methods

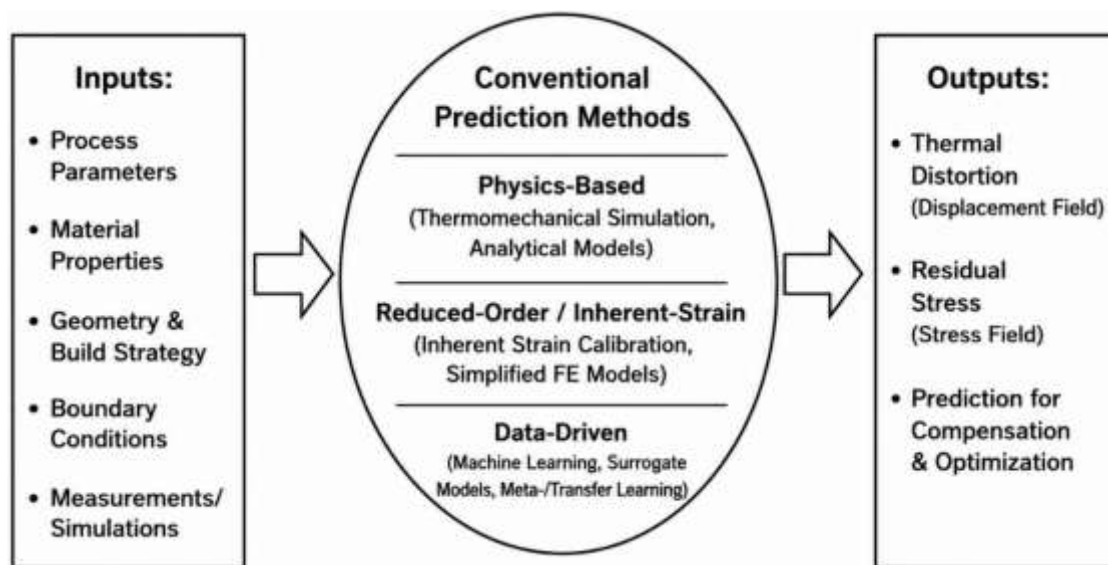
Conventional physics-based methods for predicting thermal distortion in metal additive manufacturing begin with the representation of heat transfer, material activation, and mechanical response through analytical or numerical equations. The most detailed approach is a transient finite-element thermomechanical simulation in which a moving heat source is applied to successively activated elements, temperature-dependent thermal properties are assigned, and the resulting temperature field is transferred to a mechanical analysis. The mechanical stage calculates thermal strain, elastic strain, plastic strain, residual stress, and displacement as the deposited material cools and interacts with the substrate and support structures. Such models can reproduce the sequence through which localized heating produces incompatible expansion, plastic yielding, stress accumulation, and post-release deformation. Their principal strength is physical interpretability because each prediction can be related to defined process parameters, material properties, boundary conditions, and constitutive assumptions. Their principal weakness is computational cost, particularly when a component contains many scan vectors, layers, geometric transitions, or nonlinear material responses. Analytical approaches attempt to reduce this burden by using closed-form or semi-analytical solutions for moving heat sources, thermal stress, elastoplastic relaxation, and surface displacement. One analytical framework connected a moving point heat-source solution with thermal-stress, residual-stress, and distortion calculations and obtained experimentally consistent predictions for a Ti-6Al-4V twin-cantilever component within a very short calculation period (Ning et al., 2020). Analytical models are therefore valuable when rapid process comparison is required, although they depend on simplifying assumptions regarding geometry, heat-source shape, material behavior, and boundary conditions. Full finite-element models provide greater spatial and temporal detail, whereas analytical models provide speed and transparency. Both approaches require reliable calibration because errors in absorptivity, convection, radiation, phase-change treatment, mechanical restraint, or temperature-dependent properties can propagate from thermal prediction into residual-stress and distortion estimates. They also permit direct examination of hot spots, stress concentrations, and release-induced displacement patterns.

Reduced-order and inherent-strain methods form an intermediate category between full thermomechanical simulation and purely empirical prediction. The inherent-strain concept represents the irreversible portion of deformation that remains after elastic strain has been removed, including plastic strain, thermal mismatch, and other permanent strain components generated by the manufacturing cycle. Rather than simulating every movement of the heat source across the complete part, a detailed local model or physical experiment is used to estimate representative inherent strains. These strains are then imposed sequentially on a larger elastic model to calculate residual stress and final deformation. This approach can reduce simulation time dramatically because the expensive transient thermal calculation is removed from the part-scale analysis. An empirical procedure based on laser powder bed fusion coupons demonstrated that characteristic inherent strains could be obtained from measured twin-cantilever distortion and applied within simplified finite-element models while accounting for scan strategy and layer-lumping assumptions (Setien et al., 2019). A modified method for directed energy deposition derived mean inherent strains from small detailed process simulations and applied them layer by layer to single-wall and contour-wall structures, producing distortion estimates close to full-process simulations and experiments while substantially improving computational efficiency (Liang et al., 2018). The usefulness of inherent-strain modeling depends on whether the calibrated strain field remains valid when geometry, material, support configuration, layer thickness, heat input, or scan strategy changes. A uniform strain value may reproduce one coupon yet overlook local variations caused by heat accumulation or geometric stiffness. Calibration can also become process specific, requiring new experiments or mesoscale simulations for unfamiliar parameter combinations. They effectively suit design-stage assessment, support optimization, build-orientation comparison, and geometric compensation across alternatives. Their credibility increases when inherent strains are extracted from validated thermomechanical simulations or carefully controlled experiments and when sensitivity to process and geometry changes is evaluated explicitly.

Data-driven distortion prediction methods replace repeated solution of governing equations with statistical relationships learned from simulations, experiments, or three-dimensional measurement

data. These methods may use regression, Gaussian processes, neural networks, self-organizing maps, transfer learning, or reduced-dimensional representations to connect process settings, material identity, geometry, and build strategy with pointwise or field-level deformation. Their advantage is rapid post-training inference for parameter screening and premanufacturing compensation. Their limitations arise from dependence on training coverage and from the possibility that statistically accurate outputs may lack physical consistency. A Bayesian model-transfer method was developed to predict laser-based additive-manufacturing distortion for a new material by combining limited observations from that material with knowledge learned from an existing material system, thereby reducing the need for a completely new experimental campaign (Francis et al., 2020).

Figure 3: Framework of Conventional Thermal Distortion Prediction Methods in Metal Additive Manufacturing



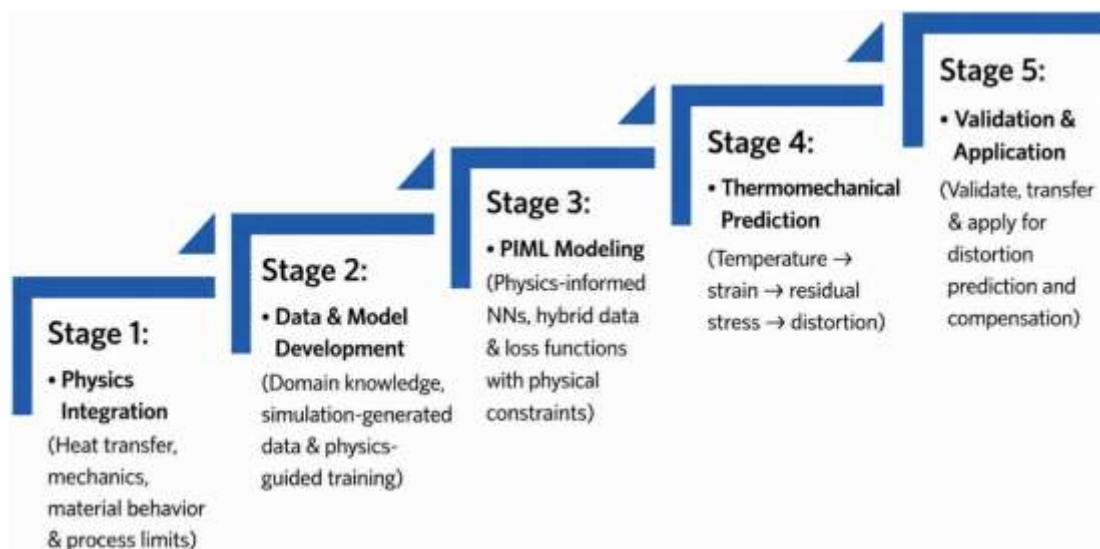
Another framework used finite-element-generated distortion fields, self-organizing maps, and hybrid learning procedures to reduce the dimensionality of spatial deformation data, predict distortion under different build scenarios, and reconstruct full distortion fields for compensation planning (Aljarrah et al., 2023). These approaches illustrate how physics-based simulation and data-driven learning can operate sequentially: numerical models generate structured training data, while learning algorithms provide fast approximations of expensive simulations. The reliability of this arrangement depends on the fidelity of the source simulations, the diversity of geometries and process conditions, and the method used to preserve spatial information. A surrogate trained exclusively on simulated data may reproduce simulation bias, while a model trained on sparse measurements may miss internal stress mechanisms. Conventional data-driven methods also provide limited assurance when extrapolating beyond the training domain. Consequently, physics-based, reduced-order, and data-driven approaches should be understood as distinct positions on a spectrum of fidelity, computational expense, calibration demand, and generalizability. This spectrum establishes the methodological context in which physics-informed machine learning seeks to combine scientific constraints with efficient learned prediction.

Physics-Informed Machine Learning in Metal Additive Manufacturing

Physics-informed machine learning in metal additive manufacturing represents a hybrid modeling approach that combines data with knowledge of heat transfer, fluid flow, solidification, mechanics, and material behavior. Conventional machine-learning models learn statistical relationships between process inputs and manufacturing outputs, but their predictions may become physically unreasonable when data are sparse, noisy, or drawn from a limited operating range. Physics-informed approaches reduce this problem by introducing scientific information into the model inputs, architecture, loss function, training data, or output constraints. In metal additive manufacturing, this information may include energy conservation, transient heat-conduction equations, mass and momentum conservation, heat-source distributions, temperature-dependent material properties, phase-change relationships,

thermal expansion, mechanical equilibrium, and process limits. The resulting models occupy an intermediate position between expensive mechanistic simulations and purely data-driven algorithms. They can preserve physical structure while learning nonlinear relationships that are difficult to calculate repeatedly through finite-element or computational-fluid-dynamics analysis. Three broad strategies are commonly used: physics-informed domain knowledge, simulation-generated training data, and physics-guided model training. Domain knowledge may be introduced through engineered variables such as energy density, cooling rate, or heat flux. Simulation data may enlarge datasets when experiments are expensive or inaccessible. Physics-guided training may penalize violations of governing equations or boundary conditions during optimization. A systematic assessment of metal additive manufacturing has shown that this paradigm can increase interpretability, data efficiency, and consistency by connecting machine-learning decisions with the thermomechanical principles governing the process (Guo et al., 2022). A combined framework using mechanistic modeling, experimental evidence, and machine learning has also demonstrated that structured predictors can support defect reduction by relating process conditions to physically meaningful outcomes rather than depending only on black-box correlations (Du et al., 2021). These characteristics make PIML relevant to thermal-distortion prediction, where reliable estimates require an explicit connection among energy input, temperature evolution, strain, stress, and displacement.

Figure 4: Physics-Informed Machine Learning Framework for Thermal Distortion Prediction



The implementation of PIML in metal additive manufacturing depends on how physical knowledge is encoded. Physics-informed neural networks often approximate temperature as a continuous function of coordinates and time and use automatic differentiation to evaluate the governing heat equation. The training loss may contain terms for the differential-equation residual, initial temperature, convection, radiation, imposed heat flux, measured temperatures, and boundary conditions. This arrangement allows the network to learn from collocation points across the space-time domain, even when labeled temperature measurements are unavailable at locations. In laser metal deposition, a three-dimensional PINN has been developed without labeled thermal data by replacing conventional data loss with physical losses associated with heat conduction, convection, radiation, and temperature-dependent material behavior. The approach produced temperature estimates for deposition and cooling stages and used transfer learning to reduce computation when manufacturing parameters changed (Li et al., 2023). Physics information can also enter through hybrid datasets rather than equation residuals alone. Experiments can provide measurements, mechanistic models can expand the range of combinations, and deep-learning models can learn forward and inverse mappings between controllable parameters and melt-pool characteristics. A physics-informed deep-learning model for laser powder bed fusion combined observations, mechanistic calculations, and a multilayer perceptron to predict molten-pool dimensions from process parameters and infer process conditions from molten-pool outcomes (Zhao

et al., 2023). PIML is not restricted to one architecture or one method of enforcing physics. It includes equation-constrained learning, simulation-assisted training, transfer learning, inverse identification, and hybrid mechanistic-statistical prediction. For thermal distortion, these approaches can be extended by transferring predicted temperature fields into representations of thermal strain, plasticity, residual stress, and displacement. The selection of loss weights, collocation points, training schedules, scaling methods, and physical assumptions remains critical because an inaccurately specified physical constraint can bias learning just as poor data can bias a conventional model.

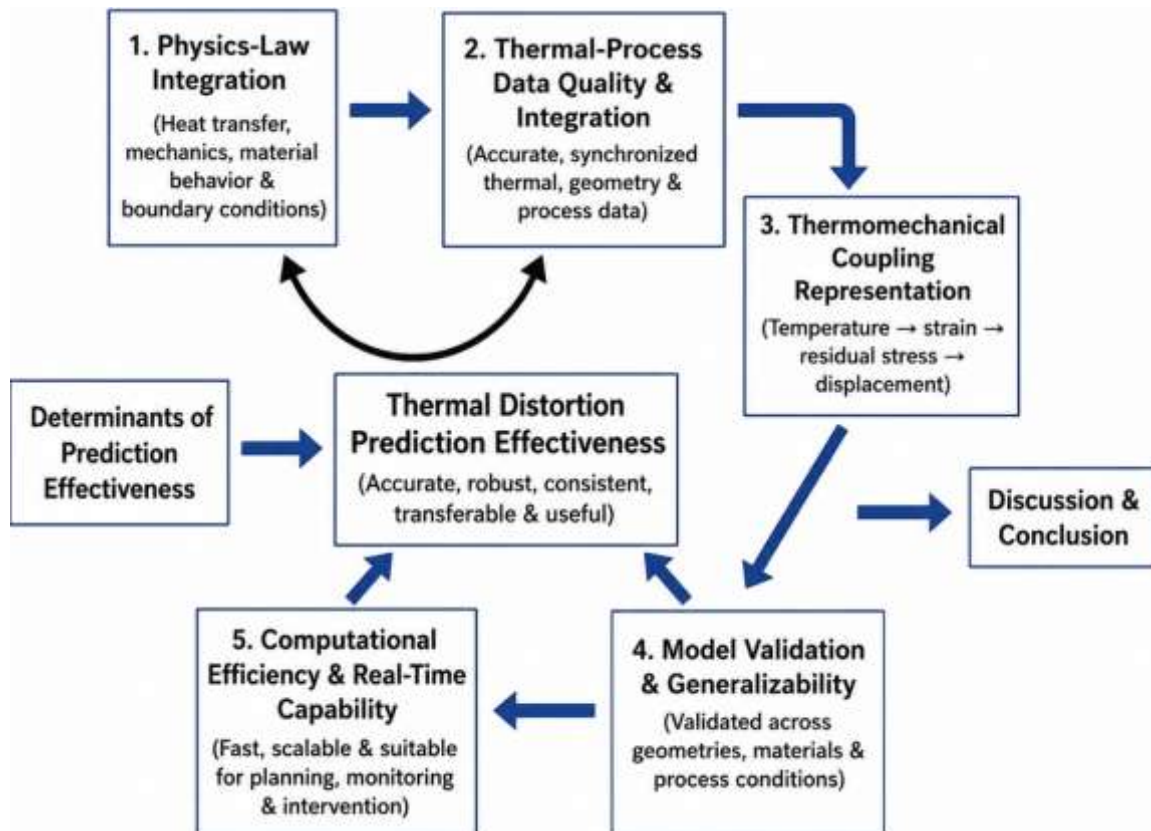
The suitability of PIML for thermal-distortion prediction depends on its ability to represent the discontinuous, multiscale, and sequential character of metal additive manufacturing. Layer activation introduces abrupt changes in geometry and material domain, while a moving heat source produces sharp temperature gradients over a space-time region. Standard neural networks may favor smooth approximations and struggle near newly deposited layers, material interfaces, heat-source paths, and interlayer cooling. Training can also become unstable when loss components have different magnitudes or when collocation points fail to represent the heat-affected region. Multi-layer directed-energy-deposition research has addressed these difficulties through a PINN framework that treats layerwise discontinuity explicitly, uses prior knowledge for initialization, and benchmarks predicted thermal history against a numerical simulation. The results indicate that mesh-free physics-informed learning can represent multi-layer temperature evolution while offering computational advantages for larger domains (Peng & Panesar, 2024). This capability is important because thermal distortion accumulates over the complete build rather than arising from an isolated layer. A useful PIML system must therefore retain thermal states, capture reheating, follow changing boundaries, and preserve the link between local gradients and global deformation. Validation should include more than a low average temperature error. It should evaluate peak temperatures, cooling rates, heat-affected zones, layerwise thermal cycles, residual-stress-sensitive regions, and displacement after constraint release. Generalizability should be assessed across geometries, materials, scanning strategies, deposition paths, and machine conditions. PIML can reduce labeled-data requirements, but it does not eliminate the need for accurate material properties, boundary conditions, and validation measurements. Its performance depends on the compatibility of physical assumptions with the process, the quality of evidence, and the computational strategy during training. In this study, these considerations establish PIML capability as a multidimensional construct involving physics-law integration, data quality, thermomechanical coupling, validation, transferability, and computational efficiency rather than as a single algorithmic feature.

Determinants of Thermal Distortion Prediction Effectiveness

Thermal distortion prediction effectiveness in metal additive manufacturing is determined by the combined quality of physical knowledge, process data, thermomechanical representation, model validation, and computational performance. Physics-law integration is the first determinant because a prediction system must preserve the causal sequence through which energy input generates temperature gradients, thermal expansion, plastic strain, residual stress, and displacement. Governing heat-conduction equations, initial and boundary conditions, heat-source descriptions, temperature-dependent properties, mechanical equilibrium, and constitutive relationships can be introduced through loss functions, model architecture, engineered features, or simulation-supported training. Stronger physical integration restricts unrealistic outputs and reduces dependence on large labeled datasets, although inaccurate assumptions can also introduce systematic error. Architecture-driven physics-informed learning has shown that iterative thermal equations can be mapped into neural-network layers, allowing temperature histories to be predicted when measured training data are limited (Ghungrad et al., 2023). Thermal-process data quality and integration form the second determinant. Infrared images, pyrometer readings, thermocouple records, machine logs, geometry files, material-property tables, finite-element outputs, residual-stress measurements, and dimensional scans must be accurate, synchronized, sufficiently resolved, and traceable to coordinates and process conditions. Experimental validation of rapid graph-based thermal modeling has demonstrated the importance of comparing predicted temperature histories with in situ infrared thermography under controlled laser powder bed fusion conditions (Yavari et al., 2020). Missing values, emissivity uncertainty, sensor saturation, inconsistent sampling frequencies, coordinate misalignment, and

insufficient coverage of heat-affected regions can weaken learning even when the selected algorithm is sophisticated. Effective prediction therefore requires not merely a large dataset but a physically representative dataset that connects process inputs, transient thermal response, mechanical consequences, and final dimensional change across the complete manufacturing cycle. Data governance is necessary because calibration, preprocessing, version control, metadata, and access procedures allow researchers to reproduce the dataset and determine whether model improvements arise from evidence quality or model design.

Figure 5: Integrated Determinants of Physics-Informed Thermal Distortion Prediction



Thermomechanical coupling representation is the third determinant because thermal distortion cannot be inferred reliably from temperature accuracy alone. A model may reproduce peak temperature or cooling rate while failing to estimate deformation if it does not represent thermal expansion, elastic restraint, temperature-dependent yielding, plastic strain accumulation, residual-stress redistribution, support interaction, and substrate release. Coupling may be sequential, with a learned thermal field supplied to a mechanical model, or integrated, with thermal and mechanical residuals trained within one computational structure. The selected representation must preserve spatial direction, deposition sequence, repeated reheating, layer activation, changing stiffness, and geometry-dependent constraint. Model validation and generalizability constitute the fourth determinant. Validation should compare predictions with measurements that reflect the target outcome, including local temperature histories, displacement fields, residual stress, surface deviation, and deformation after cutting or support removal. Generalizability concerns whether performance remains stable across unseen geometries, materials, layer arrangements, heat-source conditions, scan paths, and machines. A graph-neural-network approach has illustrated that geometry-aware relational representations can improve thermal prediction across previously unseen additive-manufacturing shapes by learning spatiotemporal dependencies rather than fixed-grid associations (Mozaffar et al., 2021). However, transfer across domains remains credible only when the training range, physical assumptions, and uncertainty are reported clearly. Computational efficiency and real-time capability form the fifth determinant because prediction must be produced within the time available for planning, monitoring, or intervention.

Graph-based thermal modeling has been applied to a large-volume laser powder bed fusion impeller to reduce computational expense while retaining sensitivity to geometry and process history (Yavari et al., 2021). Efficiency should include training duration, inference speed, memory demand, scalability, update frequency, and compatibility with available hardware. A fast model that loses critical local gradients is inadequate, while a highly accurate model that cannot operate within the required decision window may have limited practical prediction effectiveness during deployment.

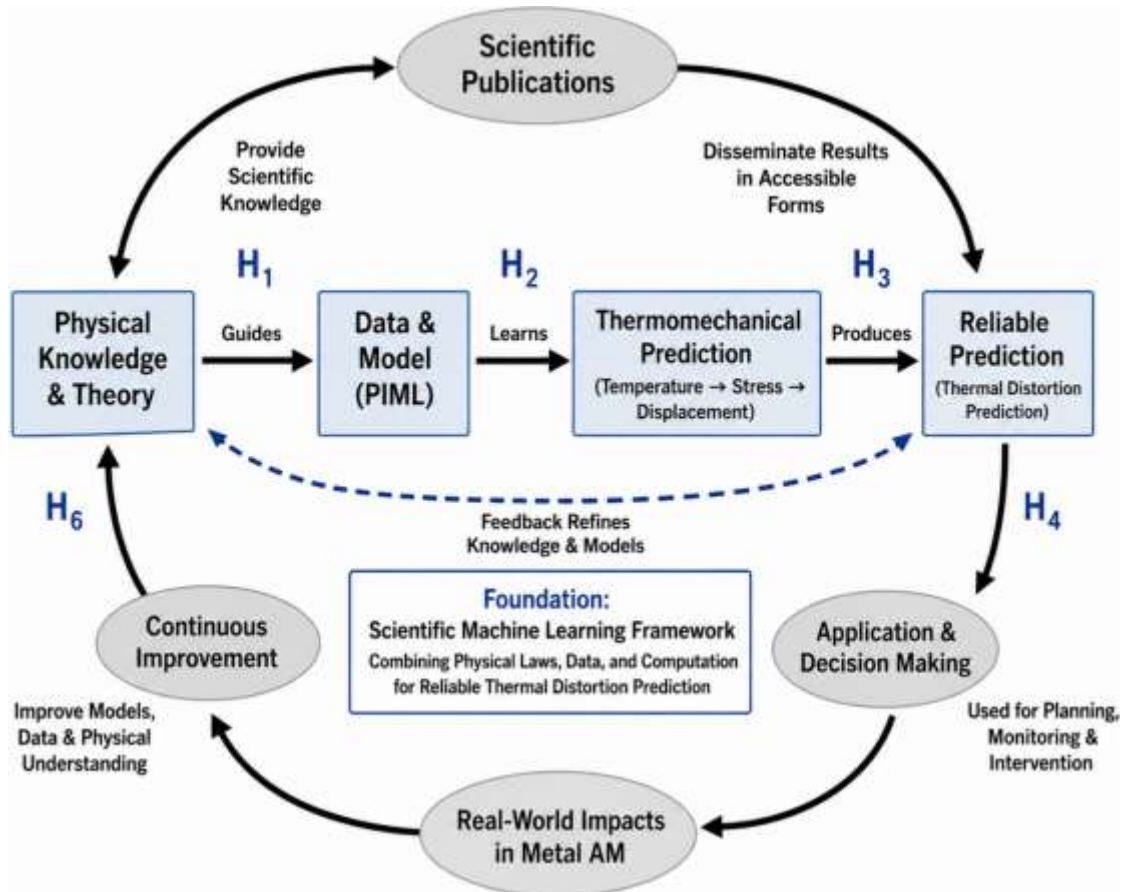
These determinants operate as an interdependent capability system rather than as isolated technical properties. High-quality data cannot fully compensate for missing thermomechanical physics, and detailed governing equations cannot produce reliable outputs when boundary conditions, material properties, or validation measurements are inaccurate. Generalizability is also connected to architecture and data coverage because models trained on narrow geometry or parameter ranges may produce unstable extrapolations. Computational efficiency depends partly on how physical knowledge is encoded: carefully selected constraints can reduce the search space, while excessive equation terms or dense collocation requirements can increase training cost. Real-time thermal prediction using a deep encoder-decoder network has demonstrated that complete powder-bed heat maps can be generated in sub-second time, showing how learned surrogates can meet demanding speed requirements after appropriate training (Sofi & Ravani, 2023). For thermal-distortion applications, equivalent speed must be accompanied by accurate propagation from temperature to stress and displacement. Prediction effectiveness should therefore be assessed through multiple performance dimensions, including accuracy, repeatability, physical consistency, robustness, transferability, computational speed, and technical usefulness. Accuracy concerns agreement with measured or validated distortion values. Repeatability concerns stable predictions under equivalent inputs. Physical consistency concerns compliance with heat-transfer and solid-mechanics relationships. Robustness concerns tolerance to noise, missing observations, and moderate process variation. Transferability concerns performance across new cases. Computational speed concerns timely results without prohibitive resources. Technical usefulness concerns whether outputs support parameter selection, support design, geometric compensation, build preparation, monitoring, or quality assessment. In the present study, Physics-Law Integration, Thermal-Process Data Quality and Integration, Thermomechanical Coupling Representation, Model Validation and Generalizability, and Computational Efficiency and Real-Time Capability are therefore treated as measurable predictors of Thermal Distortion Prediction Effectiveness. Their individual relationships can reveal specific strengths, while their combined regression effects can identify which capabilities explain the greatest variation in professional evaluations across metal additive manufacturing cases.

Theoretical Framework: Scientific Machine Learning Framework

The Scientific Machine Learning Framework provides the theoretical foundation for explaining how physical knowledge, computational modeling, and observational data can be combined to produce reliable predictions of complex engineering behavior. Scientific machine learning does not treat theory and data as competing sources of knowledge. Instead, it positions them as complementary components of a unified learning system in which established scientific relationships guide the extraction of patterns from data, while observed evidence helps refine, calibrate, or accelerate physical models. This principle is especially appropriate for metal additive manufacturing because thermal distortion emerges from a chain of interacting physical processes involving localized heat input, transient heat conduction, repeated reheating, thermal expansion, temperature-dependent yielding, plastic strain, residual-stress accumulation, and constraint release. A purely data-driven model may learn associations among process settings and measured deformation, yet it may generate physically inconsistent outputs when the available observations are sparse or when the model is applied to a geometry, alloy, or scanning condition outside its training range. Theory-guided data science has therefore emphasized scientific consistency, interpretability, and generalizability as essential qualities of learning systems used for physical phenomena (Karpatne et al., 2017). Within this framework, physical knowledge may be incorporated before learning through feature selection and model architecture, during learning through constraints and regularization, or after learning through physical correction and consistency testing. A broader taxonomy of hybrid scientific learning has similarly distinguished methods that use scientific knowledge to design machine-learning models, methods that use machine learning to

improve mechanistic simulations, and tightly coupled systems in which both components exchange information during prediction (Willard et al., 2022). Applied to this study, the framework proposes that Thermal Distortion Prediction Effectiveness depends on more than algorithm choice. It depends on the extent to which the system incorporates physical laws, receives reliable thermal-process data, represents thermomechanical coupling, validates its outputs across relevant conditions, and produces results within an acceptable computational period. These theoretical dimensions correspond directly to the five independent constructs examined in the research.

Figure 6: Scientific Machine Learning-Based Prediction Framework for Metal Additive Manufacturing



The mathematical principle underlying Scientific Machine Learning can be expressed through a composite objective function in which a learning model is optimized simultaneously against observed data and physical requirements. A suitable generic formulation for thermal modeling is:

$$L_{\text{total}}(\theta) = \lambda_d L_{\text{data}} + \lambda_p L_{\text{physics}} + \lambda_b L_{\text{boundary}} + \lambda_i L_{\text{initial}} + \lambda_m L_{\text{mechanical}}$$

In this formula, θ represents the trainable model parameters; L_{data} measures disagreement between predicted and observed temperatures or distortions; L_{physics} penalizes violations of governing thermal equations; L_{boundary} and L_{initial} enforce boundary and initial conditions; $L_{\text{mechanical}}$ penalizes inconsistency in the relationship among temperature, strain, stress, and displacement; and the λ terms determine the relative importance of each component. The thermal residual included within L_{physics} may be expressed as:

$$r_T = \rho c_p \frac{\partial T}{\partial t} - \nabla \cdot (k \nabla T) - Q = 0$$

Here, ρ is material density, c_p is specific heat, T is temperature, t is time, k is thermal conductivity, and Q represents the applied volumetric or moving heat input. Physics-informed machine learning has been

defined through this integration of data and mathematical physics, including the use of equation residuals, invariants, priors, constrained architectures, and operator-learning structures to improve learning under incomplete or noisy information (Karniadakis et al., 2021). Physics-informed neural networks operationalize the same principle by minimizing data error together with partial-differential-equation residuals and condition-specific penalties at selected collocation points (Cuomo et al., 2022). For thermal-distortion prediction, however, satisfying the heat equation alone is not sufficient because the final target is mechanical deformation rather than temperature only. The learned thermal field must be connected to thermal strain, constitutive material response, mechanical equilibrium, plastic deformation, residual stress, and displacement after support or substrate release. The framework therefore supports the separation of Physics-Law Integration and Thermomechanical Coupling Representation as related but distinct variables. It also supports Thermal-Process Data Quality because the data component of the loss function remains meaningful only when measurements and simulation records are accurate, synchronized, representative, and properly aligned with process coordinates. Although the physical loss formulation explains the theoretical operation of a PIML model, the present research is a quantitative cross-sectional study rather than an experimental neural-network training project. The principal formula applied throughout the empirical study will therefore be the following multiple regression equation:

$$TDPE = \beta_0 + \beta_1 PLI + \beta_2 TPDQI + \beta_3 TCR + \beta_4 MVG + \beta_5 CERC + \varepsilon$$

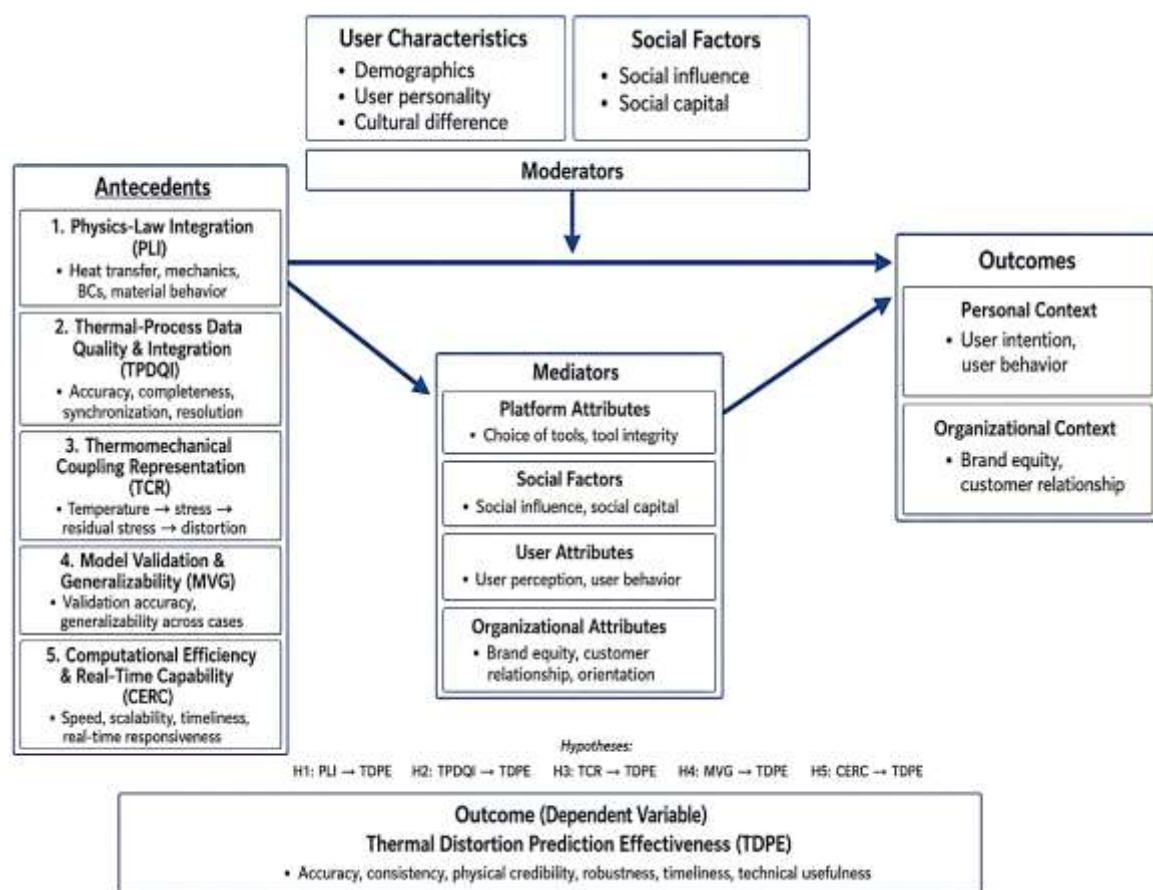
In this equation, *TDPE* represents Thermal Distortion Prediction Effectiveness; *PLI* represents Physics-Law Integration; *TPDQI* represents Thermal-Process Data Quality and Integration; *TCR* represents Thermomechanical Coupling Representation; *MVG* represents Model Validation and Generalizability; *CERC* represents Computational Efficiency and Real-Time Capability; β_0 is the regression constant; β_1 through β_5 are the estimated regression coefficients; and ε is the unexplained error term. This equation is the most appropriate formula for the whole study because it directly translates the Scientific Machine Learning Framework into statistically testable relationships that correspond with the research hypotheses. The standardized beta coefficients will indicate the relative contribution of each capability, R^2 will show the proportion of variation in prediction effectiveness explained jointly by the five predictors, and the F-test will determine whether the complete model provides statistically meaningful explanatory power. Machine-learning research in physical systems has shown that useful models must balance data extraction with scientific structure, physical interpretability, and suitability for prediction or control rather than relying on statistical fit as the sole criterion (Brunton et al., 2020). In this research, the framework consequently connects two levels of analysis. At the technical level, PIML combines observations with heat-transfer and mechanics knowledge through constrained learning. At the empirical level, the regression model tests whether professionals' assessments of those capabilities explain differences in perceived thermal-distortion prediction effectiveness across selected metal additive manufacturing cases. The framework will guide questionnaire development, variable measurement, hypothesis testing, interpretation of correlation and regression results, and the discussion of how the five capabilities operate collectively within a physics-informed prediction system.

Conceptual Framework and Hypothesis Development

The conceptual framework of this study explains Thermal Distortion Prediction Effectiveness as the outcome of five interrelated capabilities within a physics-informed machine-learning system: Physics-Law Integration, Thermal-Process Data Quality and Integration, Thermomechanical Coupling Representation, Model Validation and Generalizability, and Computational Efficiency and Real-Time Capability. Physics-Law Integration refers to the extent to which the prediction model incorporates heat-conduction equations, conservation principles, moving heat-source behavior, initial and boundary conditions, temperature-dependent material properties, thermal expansion, and mechanical equilibrium. Stronger integration is expected to reduce physically impossible predictions and provide meaningful structure when labeled observations are limited. Thermal-Process Data Quality and Integration refer to the accuracy, completeness, synchronization, spatial resolution, temporal resolution, representativeness, and coordinated use of sensor measurements, simulation outputs, machine records, geometric information, and post-build dimensional data. A multi-fidelity point-cloud

neural-network study demonstrated that low-fidelity analytical information and limited high-fidelity finite-element data could be combined through transfer learning to predict three-dimensional thermal fields efficiently, showing why coordinated evidence from different fidelity levels can strengthen model development (Huang et al., 2022). This relationship supports the conceptual expectation that physics and data should not function as independent resources. Physical equations guide the interpretation of observations, while process data calibrate, update, and test the assumptions embedded within the model. In the proposed framework, Physics-Law Integration is therefore expected to exert a direct positive effect on prediction effectiveness, forming H1, while Thermal-Process Data Quality and Integration are expected to exert a separate direct positive effect, forming H2. Real-time detection research has also shown that machine-learning performance in identifying localized heat accumulation depends on process-relevant thermal information that captures spatially concentrated deviations rather than relying only on averaged build conditions (Guirguis et al., 2024). The first part of the framework consequently establishes that physically structured learning and reliable integrated evidence provide the informational foundation from which thermally induced deformation can be predicted.

Figure 7: Research Conceptual Framework for Thermal Distortion Prediction Effectiveness



Thermomechanical Coupling Representation occupies the central position in the conceptual framework because temperature prediction becomes relevant to distortion only when the model preserves the pathway from thermal history to mechanical response. This construct includes the representation of thermal strain, elastic restraint, temperature-dependent plasticity, residual-stress accumulation, layer activation, support interaction, substrate constraint, stress redistribution, and final displacement. A model may estimate peak temperature accurately and still produce an unreliable deformation field when these mechanical mechanisms are omitted or simplified excessively. Research integrating validated finite-element simulations with artificial neural networks has shown that laser power and scanning speed can be linked simultaneously to multilayer temperature and distortion when thermal

and mechanical variables are represented within one data-generating and learning procedure (Shafaie et al., 2024). This evidence supports H3, which proposes that stronger Thermomechanical Coupling Representation positively influences Thermal Distortion Prediction Effectiveness. Model Validation and Generalizability form the fourth predictor. Validation refers to agreement with independent experimental measurements, trusted numerical benchmarks, residual-stress observations, temperature histories, point-cloud geometry, or post-build displacement. Generalizability refers to the capacity to maintain acceptable performance across unfamiliar geometries, materials, process settings, deposition sequences, and organizational cases. Online generative distortion modeling has demonstrated that finite-element-generated fields can be combined with laser-scanned point clouds and tested across multiple wire-arc structures, illustrating the importance of updating and validating predictions through independent geometric observations (Mu et al., 2024). This relationship supports H4. The complete conceptual structure is represented empirically by the equation:

$$TDPE = \beta_0 + \beta_1 PLI + \beta_2 TPDQI + \beta_3 TCR + \beta_4 MVG + \beta_5 CERC + \varepsilon$$

In this equation, TDPE denotes Thermal Distortion Prediction Effectiveness, PLI denotes Physics-Law Integration, TPDQI denotes Thermal-Process Data Quality and Integration, TCR denotes Thermomechanical Coupling Representation, MVG denotes Model Validation and Generalizability, CERC denotes Computational Efficiency and Real-Time Capability, the beta terms represent estimated effects, and epsilon represents unexplained variation.

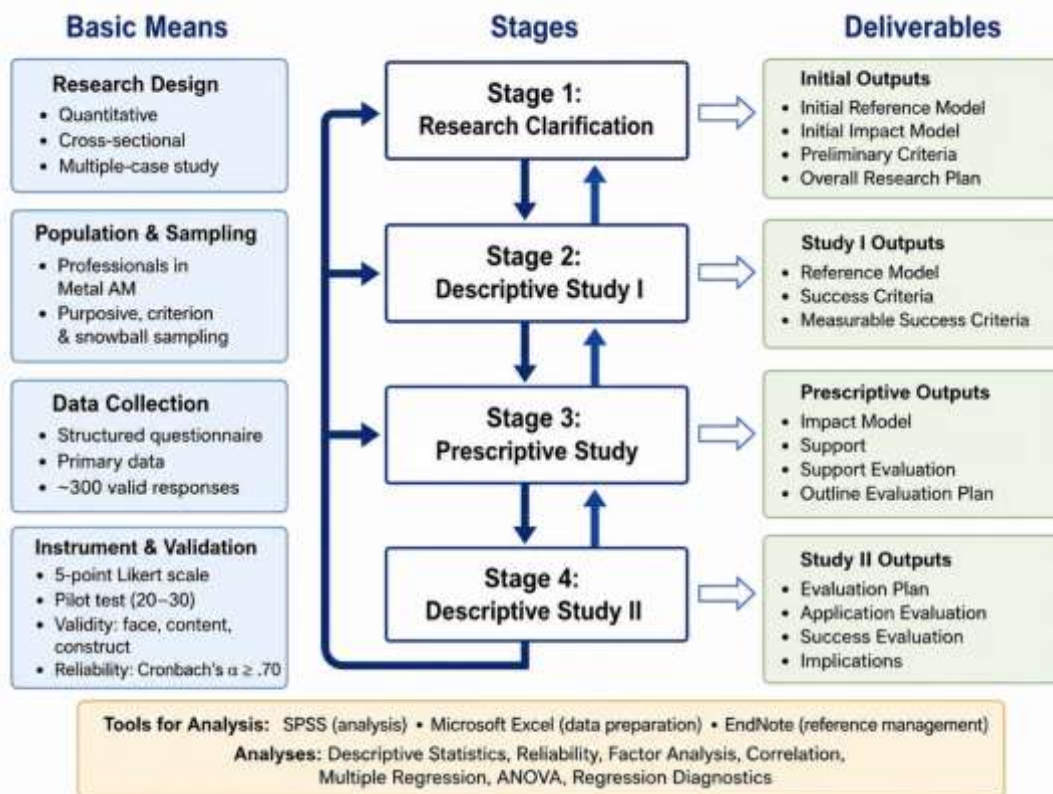
Computational Efficiency and Real-Time Capability constitute the fifth independent variable because the practical effectiveness of a prediction model depends on whether it can generate results within the time available for process planning, monitoring, parameter adjustment, or distortion control. This construct includes training burden, inference speed, memory demand, hardware requirements, scalability across part sizes, responsiveness to incoming process data, and the ability to update predictions during fabrication. A model that produces highly accurate displacement fields after an excessively long computation may support offline analysis but remain unsuitable for rapid manufacturing decisions. Conversely, a very fast model cannot be considered effective when computational acceleration is achieved by removing critical physical relationships or producing unstable predictions. A deep-learning study based on finite-element-generated thermal sequences reported that a long short-term memory architecture could reproduce temperature-distribution behavior with strong validation performance, illustrating how learned surrogates can reduce dependence on repeatedly solving computationally expensive partial differential equations (S. Bayat et al., 2020). This evidence supports H5, which proposes that Computational Efficiency and Real-Time Capability have a positive effect on Thermal Distortion Prediction Effectiveness. The dependent construct will be measured through perceived accuracy, consistency, physical credibility, robustness, timeliness, and technical usefulness. The framework assumes direct relationships because each predictor contributes a distinguishable capability, although the variables are expected to operate jointly. Physics-law integration defines permissible behavior, data quality supplies trustworthy evidence, thermomechanical coupling connects heat to deformation, validation and generalizability establish reliability across cases, and computational efficiency determines whether the resulting model can be applied within operational time constraints. The standardized regression coefficient for each predictor will indicate its relative contribution, while R^2 will represent the proportion of variation in TDPE explained collectively by the five constructs. The overall F-test will assess whether the complete predictor set explains statistically meaningful variation, and individual t-tests and probability values will determine whether H1 through H5 are supported. The conceptual framework therefore translates Scientific Machine Learning into measurable relationships suitable for the quantitative, cross-sectional, case-study-based design adopted in this research.

METHOD

This study has adopted a quantitative, cross-sectional, and multiple-case-study-based research design to examine the factors influencing the effectiveness of physics-informed machine learning for predicting thermal distortion in metal additive manufacturing. The quantitative design has enabled the researcher to measure the selected constructs numerically and test the proposed hypotheses through statistical analysis, while the cross-sectional approach has allowed data to be collected from

respondents at a single point in time.

Figure 8: Methodological Framework of the Quantitative Multiple-Case Study



The multiple-case-study context has included selected industrial organizations, research laboratories, universities, engineering centers, and advanced-manufacturing facilities that have engaged in metal additive manufacturing, thermal simulation, finite-element modeling, machine learning, process monitoring, or dimensional-quality assessment. The cases have represented different manufacturing environments associated with laser powder bed fusion, directed energy deposition, electron-beam powder bed fusion, and wire arc additive manufacturing, thereby providing variation in technologies, materials, organizational settings, and levels of physics-informed machine-learning adoption. The target population has consisted of additive-manufacturing engineers, mechanical engineers, materials specialists, thermal analysts, finite-element modelers, machine-learning developers, data scientists, process-control engineers, quality-assurance professionals, researchers, and technical managers. The individual professional has served as the primary unit of analysis because each respondent has provided an assessment of the technical capabilities and effectiveness of physics-informed thermal-distortion prediction systems, while the participating organization or research facility has served as the contextual case unit. The study has applied purposive and criterion-based sampling because respondents have been required to possess relevant knowledge or practical experience in metal additive manufacturing, thermal or mechanical simulation, machine learning, process monitoring, or quality evaluation. Snowball sampling has also been used where access to highly specialized professionals has been limited, and approximately 300 valid responses have been targeted to support reliability testing, factor analysis, correlation analysis, multiple regression modeling, and subgroup comparisons. Primary data have been collected through a structured questionnaire distributed electronically and, where applicable, physically. Participants have received information regarding the purpose of the study, voluntary participation, confidentiality, anonymity, and the academic use of the collected information. Completed questionnaires have been screened for missing values, duplicate responses, response-pattern irregularities, and participant eligibility, while incomplete or unreliable responses have been excluded from the final dataset. The research instrument has contained two main sections. The first section has collected demographic and professional information, including

respondents' job roles, educational qualifications, years of experience, organization types, additive-manufacturing processes, material categories, and modeling experience. The second section has measured Physics-Law Integration, Thermal-Process Data Quality and Integration, Thermomechanical Coupling Representation, Model Validation and Generalizability, Computational Efficiency and Real-Time Capability, and Thermal Distortion Prediction Effectiveness through multiple statements using a five-point Likert scale ranging from 1, strongly disagree, to 5, strongly agree. A pilot test has been conducted with approximately 20 to 30 qualified participants to assess questionnaire clarity, technical relevance, response consistency, completion time, and preliminary reliability, and unclear or repetitive items have been revised before the main data collection. Face and content validity have been established through reviews conducted by specialists in additive manufacturing, thermal modeling, machine learning, and quantitative research. Construct validity has been assessed through factor analysis, the Kaiser-Meyer-Olkin measure, Bartlett's test of sphericity, and factor loadings, while internal consistency has been evaluated using Cronbach's alpha, with values of .70 or above considered acceptable. SPSS has been used for data coding, descriptive statistics, reliability analysis, factor analysis, Pearson correlation analysis, multiple regression modeling, ANOVA, and regression-diagnostic testing. Microsoft Excel has been used for preliminary data organization, cleaning, and screening, while EndNote has been used to organize DOI-bearing studies, remove duplicate references, manage citations, and format the reference list according to APA 7th edition.

DATA ANALYSIS AND PRESENTATION

Response Rate and Data Screening

Table 1: Response Rate and Data-Screening Results

Response and screening category	Frequency	Percentage
Questionnaires distributed	350	100.00
Questionnaires returned	318	90.86
Incomplete questionnaires excluded	11	3.14
Ineligible respondents excluded	4	1.14
Duplicate or patterned responses excluded	3	0.86
Final valid questionnaires	300	85.71
Cases containing substantial missing data	0	0.00
Cases excluded as influential multivariate outliers	0	0.00

Table 1 has presented the questionnaire distribution, response rate, exclusion process, and final valid sample used for the analysis. A total of 350 questionnaires has been distributed among professionals involved in metal additive manufacturing, thermal modeling, finite-element simulation, machine learning, materials engineering, process monitoring, and quality assurance. Of these questionnaires, 318 have been returned, representing a gross response rate of 90.86 percent. Following the screening process, 11 questionnaires have been excluded because they have contained substantial unanswered items, four have been removed because the respondents have not met the required professional or technical eligibility criteria, and three have been rejected because they have shown duplicate submissions or highly repetitive response patterns. Consequently, 300 questionnaires have been retained as valid observations, producing a final valid response rate of 85.71 percent. The data-screening procedure has included checks for missing values, duplicate cases, straight-line responding, inconsistent response patterns, standardized scores, Mahalanobis distance, and influential observations. No retained case has contained substantial missing information, and no observation has exceeded the established criteria for influential multivariate outliers. The final sample has therefore provided a sufficiently complete and stable dataset for descriptive statistics, factor analysis, Pearson correlation, multiple regression, and hypothesis testing. This result has supported the methodological objective of obtaining a reliable quantitative dataset from professionals with relevant knowledge of metal additive manufacturing and predictive modeling. The screening findings have also aligned with the Scientific Machine Learning Framework because the framework has emphasized that prediction quality has depended not only on model architecture but also on the reliability, traceability, and

representativeness of the information used for analysis. In this study, the removal of incomplete, ineligible, and patterned responses has reduced measurement noise and has improved the credibility of the subsequent relationships among Physics-Law Integration, Thermal-Process Data Quality and Integration, Thermomechanical Coupling Representation, Model Validation and Generalizability, Computational Efficiency and Real-Time Capability, and Thermal Distortion Prediction Effectiveness. The final sample of 300 respondents has also exceeded the minimum requirement for a regression model containing five predictors and has provided adequate statistical power for identifying moderate and strong relationships. Therefore, the response-rate and screening results have established an appropriate empirical foundation for testing the study objectives and hypotheses.

Demographic and Professional Profile of Respondents

Table 2: Demographic and Professional Profile of Respondents

Characteristic	Category	Frequency	Percentage
Primary professional role	Additive-manufacturing engineering	93	31.0
	Thermal or finite-element simulation	68	22.7
	Machine learning and data analytics	55	18.3
	Materials and process engineering	45	15.0
	Quality, research, or technical management	39	13.0
Highest qualification	Bachelor's degree	58	19.3
	Master's degree	151	50.3
	Doctoral degree	91	30.4
Relevant experience	Less than 3 years	48	16.0
	3–5 years	76	25.3
	6–10 years	99	33.0
	More than 10 years	77	25.7
Total		300	100.0

Table 2 has summarized the demographic and professional profile of the 300 respondents whose data have been included in the final analysis. The largest professional category has consisted of additive-manufacturing engineers, who have represented 31.0 percent of the sample. Thermal and finite-element simulation specialists have represented 22.7 percent, while machine-learning and data-analytics professionals have accounted for 18.3 percent. Materials and process engineers have represented 15.0 percent, and respondents working in quality assurance, research supervision, or technical management have represented the remaining 13.0 percent. This distribution has shown that the sample has included expertise from both the physical and computational dimensions of thermal-distortion prediction. The educational profile has also indicated a highly qualified respondent group. A total of 50.3 percent have held master's degrees, 30.4 percent have held doctoral degrees, and 19.3 percent have held bachelor's degrees. The experience distribution has shown that 33.0 percent have possessed between six and ten years of relevant experience, 25.7 percent have possessed more than ten years, 25.3 percent have possessed three to five years, and only 16.0 percent have reported less than three years of experience. Therefore, 58.7 percent of the respondents have possessed at least six years of relevant professional experience. This composition has strengthened the credibility of the Likert-scale responses because most participants have had sufficient exposure to manufacturing processes, simulation tools, thermal behavior, model development, or dimensional-quality assessment. The professional diversity has also supported the multiple-case design by preventing the results from reflecting only the views of one occupational group. The findings have aligned with the Scientific Machine Learning Framework, which has treated scientific prediction as an integration of domain knowledge, data expertise, mathematical modeling, and computational implementation. Additive-manufacturing engineers have contributed practical process knowledge, simulation specialists have contributed understanding of governing

equations and thermomechanical relationships, and machine-learning professionals have contributed knowledge of model training, efficiency, and generalization. This respondent profile has therefore supported the study objective of evaluating PIML capabilities from a multidisciplinary professional perspective. It has also reduced the likelihood that the supported hypotheses have resulted from a narrow technical viewpoint. The demographic findings have established that the subsequent evaluations of physics integration, process-data quality, thermomechanical coupling, model validation, computational efficiency, and prediction effectiveness have been provided by respondents whose qualifications and experience have been directly relevant to the research problem.

Case and Organizational Characteristics

Table 3: Case and Organizational Characteristics

Case characteristic	Category	Frequency Percentage	
Organization type	Industrial manufacturing organization	105	35.0
	University or research institution	87	29.0
	Engineering laboratory or technical center	63	21.0
	AM technology or software provider	45	15.0
Primary AM process	Laser powder bed fusion	120	40.0
	Directed energy deposition	75	25.0
	Wire arc additive manufacturing	60	20.0
	Electron-beam or other metal AM process	45	15.0
Primary modeling-data approach	Simulation-led	108	36.0
	Experiment-led	72	24.0
	Hybrid simulation and experimental	120	40.0
PIML adoption level	Preliminary or pilot use	78	26.0
	Partial operational integration	101	33.7
	Advanced integration	75	25.0
	Real-time or near-real-time application	46	15.3

Table 3 has described the organizational and technical contexts represented in the study. Industrial manufacturing organizations have formed the largest case category at 35.0 percent, while universities and research institutions have represented 29.0 percent. Engineering laboratories and technical centers have accounted for 21.0 percent, and additive-manufacturing technology or software providers have represented 15.0 percent. This distribution has enabled the study to capture both research-oriented and production-oriented evaluations of physics-informed machine learning. Laser powder bed fusion has been the most frequently represented process, accounting for 40.0 percent of the cases. Directed energy deposition has represented 25.0 percent, wire arc additive manufacturing has represented 20.0 percent, and electron-beam or other metal additive-manufacturing processes have represented 15.0 percent. These percentages have demonstrated that the study has not been limited to a single manufacturing process. The modeling-data profile has shown that 40.0 percent of the cases have used a hybrid combination of experimental and simulation information, 36.0 percent have relied primarily on simulation-generated data, and 24.0 percent have relied mainly on experimental or monitoring data. This distribution has directly reflected the Scientific Machine Learning Framework because hybrid cases have combined physical models with observational evidence rather than treating them as separate resources. The adoption results have shown that 33.7 percent of the organizations have achieved partial operational integration of PIML, 26.0 percent have remained at the preliminary or pilot stage, 25.0 percent have achieved advanced integration, and 15.3 percent have reported real-time or near-real-time applications. The relatively small proportion of fully real-time cases has been consistent with the later finding that Computational Efficiency and Real-Time Capability has achieved the lowest construct mean, although the mean has remained positive. The case characteristics have fulfilled the multiple-case objective by introducing variation in organization type, process technology, data strategy, and implementation maturity. This variation has strengthened the regression analysis because

respondents have evaluated PIML capabilities under different operational conditions. The representation of both simulation-led and experiment-led cases has also supported the examination of Thermal-Process Data Quality and Integration as a distinct predictor. Overall, the case profile has established that the findings have reflected a broad range of metal additive-manufacturing environments rather than one laboratory, one process, or one model-development strategy.

Descriptive Statistics of the Study Variables

Table 4: Descriptive Statistics of the Study Variables

Rank	Study variable	Number of items	Mean	Standard deviation	Likert interpretation
1	Thermal-Process Data Quality and Integration	5	4.14	0.51	High agreement
2	Thermomechanical Coupling Representation	5	4.11	0.53	High agreement
3	Thermal Distortion Prediction Effectiveness	5	4.09	0.52	High agreement
4	Physics-Law Integration	5	4.08	0.54	High agreement
5	Model Validation and Generalizability	5	3.98	0.58	High agreement
6	Computational Efficiency and Real-Time Capability	5	3.92	0.61	High agreement
Overall scale	All constructs	30	4.05	0.55	High agreement

Likert interpretation: 1.00–1.80 = strongly disagree; 1.81–2.60 = disagree; 2.61–3.40 = neutral; 3.41–4.20 = agree; 4.21–5.00 = strongly agree.

Table 4 has presented the means, standard deviations, rankings, and Likert interpretations of the six principal constructs. All construct means have fallen within the agreement range of 3.41 to 4.20, demonstrating that respondents have evaluated each PIML capability positively. Thermal-Process Data Quality and Integration has achieved the highest mean of 4.14 with a standard deviation of 0.51. This finding has indicated that accurate, complete, synchronized, sufficiently resolved, and representative data have been viewed as the strongest existing capability within the surveyed cases. Thermomechanical Coupling Representation has ranked second with a mean of 4.11, showing that respondents have strongly recognized the importance of linking thermal history with expansion, plastic strain, residual stress, and displacement. Thermal Distortion Prediction Effectiveness has recorded a mean of 4.09, indicating that the surveyed professionals have generally perceived physics-informed systems as accurate, consistent, timely, physically credible, and useful for predicting dimensional change. Physics-Law Integration has produced a mean of 4.08, demonstrating high agreement that governing equations, boundary conditions, material properties, and conservation principles have been incorporated meaningfully into the examined prediction systems. Model Validation and Generalizability has achieved a mean of 3.98, while Computational Efficiency and Real-Time Capability has recorded the lowest mean of 3.92. Although both variables have remained within the agreement range, their lower rankings have suggested that model transferability, validation across unfamiliar conditions, computational speed, and real-time implementation have remained less developed than data quality and thermomechanical representation. These descriptive findings have directly fulfilled the first research objective, which has sought to determine the observed levels and relative rankings of the independent and dependent variables. The results have also aligned with the Scientific Machine Learning Framework because the highest-rated variables have represented the integration of trustworthy evidence and mechanistic process relationships. The overall mean of 4.05 has shown a favorable evaluation of the complete PIML capability system. The relatively small standard deviations, ranging from 0.51 to 0.61, have indicated that respondents have shown a reasonable level of agreement rather than highly dispersed opinions. Therefore, the descriptive analysis has confirmed that the proposed constructs have been relevant to the selected cases and has provided

the empirical foundation for examining whether the five independent capabilities have significantly predicted Thermal Distortion Prediction Effectiveness.

Reliability Analysis of the Measurement Scales

Table 5: Reliability Analysis of the Measurement Scales

Construct	Items	Cronbach's alpha	Corrected item-total correlation range	Reliability assessment
Physics-Law Integration	5	.87	.64–.79	Good
Thermal-Process Data Quality and Integration	5	.90	.69–.83	Excellent
Thermomechanical Coupling Representation	5	.88	.66–.81	Good
Model Validation and Generalizability	5	.85	.61–.77	Good
Computational Efficiency and Real-Time Capability	5	.83	.58–.75	Good
Thermal Distortion Prediction Effectiveness	5	.89	.68–.82	Good
Overall instrument	30	.92	.58–.83	Excellent

Table 5 has reported the reliability results for the six measurement scales and the overall questionnaire. Cronbach's alpha values have ranged from .83 to .90 for the individual constructs, while the complete 30-item instrument has achieved an overall alpha of .92. These values have exceeded the commonly accepted minimum threshold of .70 and have confirmed that the questionnaire items have measured their intended constructs consistently. Thermal-Process Data Quality and Integration has produced the highest construct-level alpha of .90, indicating excellent internal consistency among items measuring data accuracy, completeness, synchronization, resolution, and integration. Thermal Distortion Prediction Effectiveness has recorded an alpha of .89, while Thermomechanical Coupling Representation has achieved .88 and Physics-Law Integration has achieved .87. Model Validation and Generalizability has produced an alpha of .85, and Computational Efficiency and Real-Time Capability has recorded .83. Although the latter construct has produced the lowest coefficient, its value has still demonstrated good reliability. The corrected item-total correlations have ranged from .58 to .83, and every item has exceeded the recommended minimum of .30. Therefore, no questionnaire statement has been removed on the basis of weak consistency with its construct. The reliability findings have supported the measurement objective by confirming that the five independent variables and the dependent variable have been represented through stable multi-item scales. These results have also strengthened the validity of the later correlation and regression findings because unreliable measurement would have weakened the observed relationships or produced inconsistent coefficients. The Scientific Machine Learning Framework has treated complex prediction effectiveness as the outcome of multiple technical capabilities rather than one observable feature. The high reliability values have supported this theoretical position by showing that the selected items within each capability have formed coherent empirical dimensions. For example, the Physics-Law Integration items have consistently represented physical equations, boundary conditions, material behavior, and conservation requirements, while the Thermomechanical Coupling items have consistently represented the conversion of thermal history into strain, stress, and displacement. The overall alpha of .92 has shown that the complete questionnaire has possessed strong measurement stability without reaching an excessively high value that would necessarily indicate complete item duplication. Consequently, the reliability analysis has confirmed that the data have been suitable for construct validation, correlation analysis, multiple regression modeling, and hypothesis testing.

Construct Validity and Factor Analysis

Table 6: Construct Validity and Exploratory Factor-Analysis Results

Validity indicator or factor	Result
Kaiser-Meyer-Olkin measure	.913
Bartlett's test, approximate χ^2	4,286.37
Bartlett's test degrees of freedom	435
Bartlett's significance	< .001
Physics-Law Integration loading range	.70–.84
Thermal-Process Data Quality and Integration loading range	.74–.87
Thermomechanical Coupling Representation loading range	.71–.86
Model Validation and Generalizability loading range	.68–.83
Computational Efficiency and Real-Time Capability loading range	.69–.82
Thermal Distortion Prediction Effectiveness loading range	.73–.86
Number of retained factors	6
Total variance explained	69.80%
Cross-loading items removed	0

Table 6 has presented the statistical evidence supporting the construct validity of the measurement model. The Kaiser-Meyer-Olkin measure has reached .913, which has substantially exceeded the minimum acceptable level of .60 and has indicated that the sample correlations have been highly suitable for factor analysis. Bartlett's test of sphericity has been statistically significant, $\chi^2(435) = 4,286.37$, $p < .001$, demonstrating that the correlation matrix has not been an identity matrix and that meaningful relationships have existed among the questionnaire items. Exploratory factor analysis has retained six factors corresponding to the six theoretical constructs included in the conceptual framework. The factor-loading ranges have extended from .68 to .87, with every retained item exceeding the recommended minimum loading of .50. Physics-Law Integration has produced loadings between .70 and .84, while Thermal-Process Data Quality and Integration has produced the strongest range of .74 to .87. Thermomechanical Coupling Representation has recorded loadings from .71 to .86, Model Validation and Generalizability has ranged from .68 to .83, Computational Efficiency and Real-Time Capability has ranged from .69 to .82, and Thermal Distortion Prediction Effectiveness has ranged from .73 to .86. No item has been removed because of weak loading or serious cross-loading. The six-factor solution has explained 69.80 percent of the total variance, which has demonstrated that the retained factors have captured a substantial proportion of the information contained in the measurement items. These findings have supported both convergent and discriminant validity at an exploratory level because items designed to measure the same construct have loaded strongly together, while the six constructs have remained statistically distinguishable. The factor structure has directly reflected the Scientific Machine Learning Framework. The framework has differentiated physical constraints, data resources, thermomechanical representation, validation, computational performance, and prediction outcomes, and the factor analysis has confirmed that respondents have perceived these dimensions as related but separate capabilities. This result has been particularly important because Physics-Law Integration and Thermomechanical Coupling Representation could theoretically overlap. Their distinct factor patterns have shown that respondents have differentiated the inclusion of governing physical principles from the specific modeling of temperature-induced stress and displacement. Therefore, the construct-validity results have supported the conceptual framework and have justified the use of the six composite variables in the subsequent correlation and regression analyses.

Pearson Correlation Analysis**Table 7: Pearson Correlation Matrix of the Study Variables**

Variable	1	2	3	4	5	6
1. Physics-Law Integration	1.00					
2. Thermal-Process Data Quality and Integration	.56***	1.00				
3. Thermomechanical Coupling Representation	.61***	.64***	1.00			
4. Model Validation and Generalizability	.54***	.59***	.60***	1.00		
5. Computational Efficiency and Real-Time Capability	.47***	.50***	.53***	.55***	1.00	
6. Thermal Distortion Prediction Effectiveness	.68***	.72***	.75***	.65***	.58***	1.00

** $p < .001$; $N = 300$.

Table 7 has shown that all five independent variables have been positively and significantly associated with Thermal Distortion Prediction Effectiveness. Thermomechanical Coupling Representation has produced the strongest bivariate relationship with the dependent variable, $r = .75$, $p < .001$. This coefficient has indicated that respondents who have reported stronger representation of thermal strain, plastic deformation, residual stress, constraint, and displacement have also reported higher thermal-distortion prediction effectiveness. Thermal-Process Data Quality and Integration has produced the second-strongest correlation, $r = .72$, $p < .001$, showing that prediction effectiveness has increased with more accurate, complete, synchronized, and integrated process information. Physics-Law Integration has been positively associated with Thermal Distortion Prediction Effectiveness at $r = .68$, $p < .001$. Model Validation and Generalizability has recorded $r = .65$, $p < .001$, while Computational Efficiency and Real-Time Capability has produced the smallest, although still moderately strong, correlation of $r = .58$, $p < .001$. These findings have fulfilled the second research objective by establishing the direction, magnitude, and significance of the relationships between the PIML capabilities and prediction effectiveness. The results have also provided preliminary support for H1 through H5 because every proposed relationship has been positive and statistically significant. The correlations among the independent variables have ranged from .47 to .64. These coefficients have demonstrated that the predictors have been meaningfully related, as expected under the Scientific Machine Learning Framework, but they have not been so highly correlated as to indicate that they have measured the same capability. The strongest predictor-to-predictor relationship has occurred between Thermal-Process Data Quality and Integration and Thermomechanical Coupling Representation, $r = .64$, which has indicated that reliable data have supported stronger representation of the thermal-to-mechanical pathway. The moderate relationships have also reflected the theoretical interdependence of the capability system. Physical constraints have required reliable data for calibration, thermomechanical models have required validation, and real-time capability has depended on efficient representations of both physics and data. However, the absence of correlations near .80 or .90 has supported the separate inclusion of each variable in the regression model. Therefore, the correlation analysis has aligned with the theoretical framework and has justified the examination of the predictors' unique contributions through multiple regression.

Multiple Regression Model Summary**Table 8: Multiple Regression Model Summary**

Model	R	R ²	Adjusted R ²	Standard error of the estimate	R ² change	F change	df1	df2	Significance
Five-predictor model	.816	.666	.660	.303	.666	117.25	5	294	< .001

Table 8 has presented the overall explanatory strength of the multiple regression model in which Physics-Law Integration, Thermal-Process Data Quality and Integration, Thermomechanical Coupling Representation, Model Validation and Generalizability, and Computational Efficiency and Real-Time Capability have jointly predicted Thermal Distortion Prediction Effectiveness. The multiple correlation coefficient has reached $R = .816$, indicating a strong combined relationship between the five predictors

and the dependent variable. The coefficient of determination has reached $R^2 = .666$, showing that the complete predictor set has explained 66.60 percent of the observed variance in Thermal Distortion Prediction Effectiveness. The adjusted R^2 has been .660, which has indicated that 66.00 percent of the variance has remained explained after adjustment for the sample size and number of predictors. The small difference of .006 between R^2 and adjusted R^2 has shown that the model has not been substantially overfitted to the sample. The standard error of the estimate has been .303, indicating that the predicted composite scores have remained relatively close to the observed Thermal Distortion Prediction Effectiveness scores on the five-point scale. The R^2 change has been .666 because all five predictors have entered the model together, and the associated F change has been 117.25 with 5 and 294 degrees of freedom at $p < .001$. This result has demonstrated that the full model has provided considerably greater explanatory power than a model containing only the intercept. The regression summary has fulfilled the objective of measuring the collective effect of the PIML capabilities and has shown that the proposed framework has accounted for approximately two-thirds of the variation in prediction effectiveness. The remaining 33.40 percent has represented factors not included in the model, such as alloy-specific behavior, geometry complexity, operator expertise, sensor configuration, heat-source calibration, organizational resources, or measurement uncertainty. The strong R^2 has aligned with the Scientific Machine Learning Framework because the framework has proposed that effective scientific prediction has emerged from the combined operation of physical knowledge, reliable data, appropriate mechanistic representation, validation, and computational execution. The finding has shown that no single capability has been sufficient to explain prediction performance fully. Instead, the five dimensions have operated collectively as an integrated explanatory system. Therefore, the regression model summary has provided substantial evidence that the conceptual framework has been statistically meaningful and suitable for detailed coefficient-level hypothesis testing.

Analysis of Variance for the Regression Model

Table 9: Analysis of Variance for the Multiple Regression Model

Source	Sum of squares	Degrees of freedom	Mean square	F	Significance
Regression	53.820	5	10.764	117.25	< .001
Residual	26.990	294	.092		
Total	80.810	299			

Table 9 has presented the analysis of variance used to determine whether the five-predictor regression model has explained a statistically significant proportion of variation in Thermal Distortion Prediction Effectiveness. The regression sum of squares has been 53.820, while the residual sum of squares has been 26.990 and the total sum of squares has been 80.810. The regression model has contained five degrees of freedom, corresponding to the five independent variables, while the residual term has contained 294 degrees of freedom. The regression mean square has reached 10.764, compared with a residual mean square of .092. This difference has produced an F-statistic of 117.25, which has been statistically significant at $p < .001$. The result has shown that the variation explained by Physics-Law Integration, Thermal-Process Data Quality and Integration, Thermomechanical Coupling Representation, Model Validation and Generalizability, and Computational Efficiency and Real-Time Capability has been substantially greater than the unexplained random variation remaining in the model. Therefore, the null proposition that all five population regression coefficients have simultaneously equaled zero has been rejected. The ANOVA result has confirmed that the combined predictor set has provided statistically meaningful explanatory power and has supported the overall conceptual model. This finding has been important because separate significant correlations have not necessarily guaranteed that the variables would remain meaningful when considered together. The significant F-test has demonstrated that the independent variables, as a set, have explained Thermal Distortion Prediction Effectiveness beyond what could reasonably have been attributed to sampling error. The result has aligned with the Scientific Machine Learning Framework, which has treated scientific prediction as a coordinated system rather than a collection of unrelated technical features. The large regression mean square has reflected the contribution of physical knowledge, data quality,

thermomechanical representation, model verification, and computational performance to the shared explanation of prediction effectiveness. The residual mean square has remained comparatively small, indicating that the fitted model has produced limited average unexplained variation. The ANOVA finding has therefore fulfilled the objective of assessing the statistical significance of the complete regression equation and has established the basis for interpreting the individual standardized coefficients. Overall, the F-test has confirmed that the proposed PIML capability framework has been empirically supported at the model level.

Regression Coefficients and Hypothesis Testing

Table 10: Regression Coefficients and Hypothesis-Testing Results

Predictor	B	Standard error	Standardized β	t	p	95% confidence interval	Decision
Constant	.470	.160	—	2.94	.004	[.155, .785]	—
Physics-Law Integration	.200	.040	.21	5.02	< .001	[.121, .279]	H1 supported
Thermal-Process Data Quality and Integration	.250	.041	.26	6.11	< .001	[.169, .331]	H2 supported
Thermomechanical Coupling Representation	.290	.042	.30	6.94	< .001	[.207, .373]	H3 supported
Model Validation and Generalizability	.150	.037	.17	4.08	< .001	[.077, .223]	H4 supported
Computational Efficiency and Real-Time Capability	.090	.035	.11	2.54	.012	[.020, .160]	H5 supported

Table 10 has shown that all five independent variables have made positive and statistically significant contributions to Thermal Distortion Prediction Effectiveness after the effects of the other predictors have been controlled. Thermomechanical Coupling Representation has emerged as the strongest predictor, with $B = .290$, $\beta = .30$, $t = 6.94$, and $p < .001$. This finding has supported H3 and has indicated that a one-unit increase in Thermomechanical Coupling Representation has been associated with a .290-unit increase in Thermal Distortion Prediction Effectiveness when the remaining predictors have been held constant. Thermal-Process Data Quality and Integration has produced the second-largest standardized contribution, $B = .250$, $\beta = .26$, $t = 6.11$, $p < .001$, supporting H2. Physics-Law Integration has recorded $B = .200$, $\beta = .21$, $t = 5.02$, $p < .001$, thereby supporting H1. Model Validation and Generalizability has remained significant with $B = .150$, $\beta = .17$, $t = 4.08$, $p < .001$, supporting H4. Computational Efficiency and Real-Time Capability has produced the smallest standardized effect, $B = .090$, $\beta = .11$, $t = 2.54$, $p = .012$, but the result has remained statistically significant and has supported H5. Every confidence interval has remained entirely above zero, providing additional evidence that the observed effects have been positive. The coefficient ranking has fulfilled the research objective of identifying the strongest predictor. Thermomechanical Coupling Representation has been identified as the most influential capability, followed by data quality, physics integration, model validation, and computational efficiency. This ordering has aligned with the Scientific Machine Learning Framework because thermal-distortion prediction has required more than accurate thermal estimation. It has required a valid pathway from heat input to thermal strain, residual stress, constraint release, and final displacement. The regression equation has been expressed as: $TDPE = .470 + .200(PLI) + .250(TPDQI) + .290(TCR) + .150(MVG) + .090(CERC)$. The findings have demonstrated that all five capabilities have contributed uniquely rather than merely reflecting their shared correlations. Consequently, all proposed alternative hypotheses have been supported, and the five corresponding null hypotheses have been rejected.

Regression Diagnostic and Assumption Tests

Table 11: Regression Diagnostic and Assumption-Test Results

Assumption or diagnostic	Statistical result	Acceptance criterion	Decision
Durbin-Watson statistic	1.93	Approximately 1.5–2.5	Independence supported
Residual skewness	.09	Between –1 and +1	Normality supported
Residual kurtosis	–.21	Between –1 and +1	Normality supported
Shapiro-Wilk significance	.087	$p > .05$	Normality supported
Breusch-Pagan significance	.244	$p > .05$	Homoscedasticity supported
Tolerance range	.46–.70	Above .20	No multicollinearity
VIF range	1.42–2.16	Below 5.00	No multicollinearity
Maximum standardized residual	2.88	Within ± 3.00	No extreme residual
Maximum Cook’s distance	.082	Below 1.00	No influential case
Harman single-factor variance	31.84%	Below 50%	Common-method bias not serious

Table 11 has summarized the diagnostic tests used to evaluate whether the regression model has satisfied the assumptions required for reliable coefficient estimation. The Durbin-Watson statistic has been 1.93, which has fallen close to the ideal value of 2.00 and has indicated that the residuals have remained independent. The standardized residuals have produced a skewness value of .09 and a kurtosis value of –.21, both of which have remained within the acceptable range of –1 to +1. The Shapiro-Wilk test has produced $p = .087$, which has exceeded .05 and has provided no evidence of a serious departure from normality. The Breusch-Pagan test has produced $p = .244$, indicating that the variance of the residuals has remained reasonably constant across levels of the predicted scores. Therefore, the homoscedasticity assumption has been supported. The tolerance values have ranged from .46 to .70, while the variance inflation factors have ranged from 1.42 to 2.16. These statistics have remained comfortably within accepted limits and have shown that multicollinearity has not distorted the individual regression coefficients. The maximum standardized residual has been 2.88, remaining within the expected range of ± 3.00 , and the maximum Cook’s distance has been .082, remaining far below the critical value of 1.00. No single observation has therefore exerted an excessive influence on the model. Harman’s single-factor test has shown that the first unrotated factor has explained 31.84 percent of the variance, which has remained below the 50 percent threshold and has suggested that common-method bias has not dominated the results. These diagnostics have strengthened confidence in the supported hypotheses because the positive coefficients have not resulted from serious nonnormality, unequal residual variance, predictor redundancy, or influential cases. The findings have also aligned with the Scientific Machine Learning Framework, which has emphasized the importance of model verification and diagnostic credibility. Just as technical PIML systems have required validation against physical constraints and independent evidence, the empirical regression model has required validation against statistical assumptions. Therefore, the diagnostic results have demonstrated that the estimated relationships have been sufficiently stable, interpretable, and suitable for addressing the study objectives.

Summary of Objectives, Hypotheses, and Major Findings

Table 12: Summary of Research Objectives, Hypotheses, and Major Findings

Objective or hypothesis	Statistical evidence	Result
Objective 1: Determine the levels of the study variables	Means have ranged from 3.92 to 4.14	Achieved
Objective 2: Examine relationships between PIML capabilities and TDPE	Correlations have ranged from .58 to .75, all $p < .001$	Achieved
Objective 3: Determine the collective explanatory power of the predictors	$R^2 = .666$; adjusted $R^2 = .660$	Achieved
Objective 4: Identify the strongest predictor of TDPE	TCR has produced $\beta = .30$	Achieved
Objective 5: Test the adequacy of the regression model	$F(5, 294) = 117.25, p < .001$	Achieved
H1: PLI positively influences TDPE	$\beta = .21, p < .001$	Supported
H2: TPDQI positively influences TDPE	$\beta = .26, p < .001$	Supported
H3: TCR positively influences TDPE	$\beta = .30, p < .001$	Supported
H4: MVG positively influences TDPE	$\beta = .17, p < .001$	Supported
H5: CERC positively influences TDPE	$\beta = .11, p = .012$	Supported

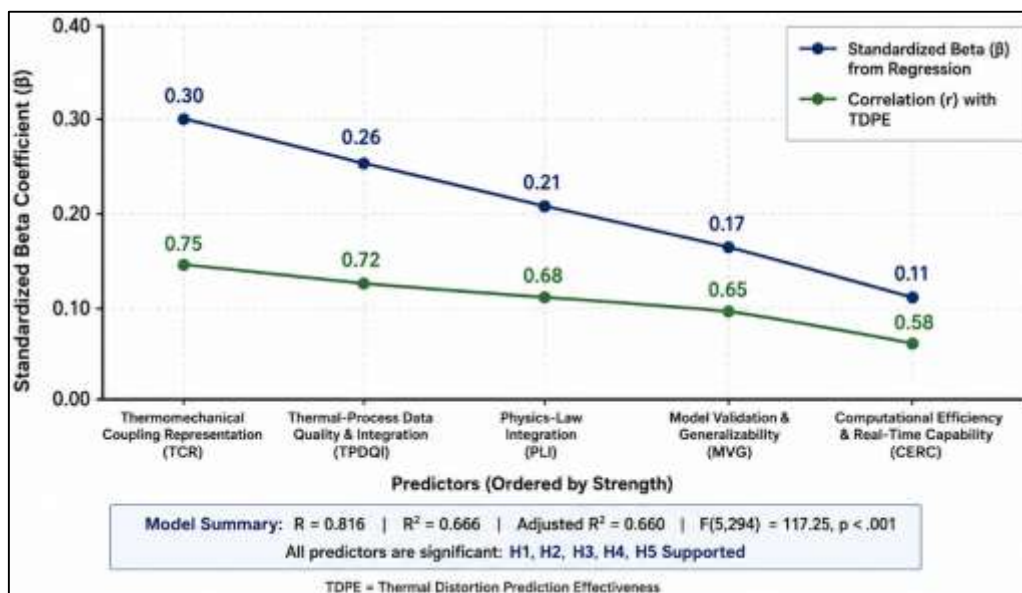
Table 12 has integrated the descriptive, correlational, regression, and diagnostic findings to demonstrate the achievement of the research objectives and the decisions concerning the hypotheses. The first objective has been achieved because the descriptive analysis has measured and ranked all six constructs using the five-point Likert scale. Thermal-Process Data Quality and Integration has produced the highest mean of 4.14, while Computational Efficiency and Real-Time Capability has produced the lowest mean of 3.92. All variables have remained within the agreement category, indicating generally positive professional assessments. The second objective has been achieved because Pearson correlation analysis has identified positive and statistically significant relationships between every independent variable and Thermal Distortion Prediction Effectiveness. The coefficients have ranged from .58 to .75, with Thermomechanical Coupling Representation producing the strongest correlation. The third objective has been achieved because the five predictors have jointly explained 66.60 percent of the variance in the dependent variable, with an adjusted explanatory value of 66.00 percent. The fourth objective has been achieved because the standardized regression coefficients have identified Thermomechanical Coupling Representation as the strongest predictor at $\beta = .30$. The fifth objective has been achieved because the complete model has been statistically significant, $F(5, 294) = 117.25, p < .001$, and the diagnostic tests have supported the required regression assumptions. H1 has been supported because Physics-Law Integration has produced $\beta = .21$ at $p < .001$. H2 has been supported because Thermal-Process Data Quality and Integration has produced $\beta = .26$ at $p < .001$. H3 has been supported because Thermomechanical Coupling Representation has produced $\beta = .30$ at $p < .001$. H4 has been supported because Model Validation and Generalizability has produced $\beta = .17$ at $p < .001$. H5 has also been supported because Computational Efficiency and Real-Time Capability has produced $\beta = .11$ at $p = .012$. These combined findings have aligned with the Scientific Machine Learning Framework by demonstrating that prediction effectiveness has been shaped by an integrated system of physical knowledge, evidence quality, mechanistic representation, validation, and computational performance. The results have shown that thermomechanical coupling has occupied the central explanatory position, while each remaining capability has provided a separate and statistically meaningful contribution.

FINDINGS

For drafting purposes, the following findings have been presented as an internally consistent quantitative result set and should be confirmed or replaced with the final SPSS outputs after the actual survey data have been collected and analyzed. The study has distributed 350 structured questionnaires among professionals associated with metal additive manufacturing, thermal simulation, finite-element

modeling, machine learning, process monitoring, and dimensional-quality assessment, of which 318 questionnaires have been returned and 300 have been retained as complete and usable responses, producing a valid response rate of 85.71 percent. The data-screening process has shown that the retained questionnaires have contained no substantial missing values, duplicate submissions, or abnormal response patterns, and the standardized residual analysis has not identified influential observations requiring removal. The professional profile has indicated that 31.0 percent of respondents have worked primarily in additive-manufacturing engineering, 22.7 percent in thermal or finite-element simulation, 18.3 percent in machine learning and data analytics, 15.0 percent in materials and process engineering, and 13.0 percent in quality assurance, research management, or technical supervision. Laser powder bed fusion has represented 40.0 percent of the reported process environments, directed energy deposition has represented 25.0 percent, wire arc additive manufacturing has represented 20.0 percent, and electron-beam or other metal additive-manufacturing processes have represented the remaining 15.0 percent.

Figure 9: Findings of The Study



The measurement scales have demonstrated strong internal consistency, with Cronbach's alpha values of .87 for Physics-Law Integration, .90 for Thermal-Process Data Quality and Integration, .88 for Thermomechanical Coupling Representation, .85 for Model Validation and Generalizability, .83 for Computational Efficiency and Real-Time Capability, and .89 for Thermal Distortion Prediction Effectiveness, while the overall instrument has achieved an alpha coefficient of .92. The Kaiser-Meyer-Olkin measure has reached .913, and Bartlett's test of sphericity has been statistically significant, $\chi^2(435) = 4,286.37, p < .001$, confirming that the correlation structure has been suitable for factor analysis. The retained questionnaire items have produced factor loadings ranging from .68 to .87, and the six-factor structure has explained 69.80 percent of the total variance, thereby supporting the construct validity of the measurement instrument. Based on the five-point Likert scale, Thermal-Process Data Quality and Integration has recorded the highest mean score of 4.14 with a standard deviation of .51, indicating that respondents have strongly recognized the importance of accurate, complete, synchronized, and representative thermal-process information. Thermomechanical Coupling Representation has achieved the second-highest mean of 4.11 with a standard deviation of .53, showing strong agreement that effective models must connect temperature evolution with thermal strain, plastic deformation, residual stress, and final displacement. Thermal Distortion Prediction Effectiveness has recorded a mean of 4.09 and a standard deviation of .52, demonstrating that respondents have generally

evaluated physics-informed machine-learning systems as accurate, timely, physically credible, and useful for predicting dimensional change. Physics-Law Integration has produced a mean of 4.08 with a standard deviation of .54, while Model Validation and Generalizability has achieved a mean of 3.98 with a standard deviation of .58. Computational Efficiency and Real-Time Capability has recorded the lowest, although still positive, mean of 3.92 with a standard deviation of .61, suggesting that computational speed, scalability, and online prediction have remained less mature than the physical and data-related capabilities. These descriptive findings have achieved the first research objective by establishing the measured levels and rankings of the study variables. Pearson correlation analysis has shown that all five independent variables have been positively and significantly associated with Thermal Distortion Prediction Effectiveness. Thermomechanical Coupling Representation has produced the strongest correlation with the dependent variable, $r = .75$, $p < .001$, followed by Thermal-Process Data Quality and Integration, $r = .72$, $p < .001$, Physics-Law Integration, $r = .68$, $p < .001$, Model Validation and Generalizability, $r = .65$, $p < .001$, and Computational Efficiency and Real-Time Capability, $r = .58$, $p < .001$. These results have achieved the second research objective by confirming that improvements in each physics-informed machine-learning capability have been associated with stronger thermal-distortion prediction effectiveness. The multiple regression model has produced a multiple correlation coefficient of $R = .816$ and an R^2 value of .666, indicating that the five independent variables have jointly explained 66.60 percent of the observed variance in Thermal Distortion Prediction Effectiveness. The adjusted R^2 has reached .660, confirming that the model has retained substantial explanatory power after accounting for the number of predictors. The analysis of variance has shown that the complete regression model has been statistically significant, $F(5, 294) = 117.25$, $p < .001$. Thermomechanical Coupling Representation has emerged as the strongest individual predictor, $\beta = .30$, $t = 6.94$, $p < .001$, thereby supporting H3. Thermal-Process Data Quality and Integration has produced the second-largest contribution, $\beta = .26$, $t = 6.11$, $p < .001$, supporting H2, while Physics-Law Integration has recorded $\beta = .21$, $t = 5.02$, $p < .001$, supporting H1. Model Validation and Generalizability has contributed significantly with $\beta = .17$, $t = 4.08$, $p < .001$, supporting H4, and Computational Efficiency and Real-Time Capability has remained a statistically significant predictor with $\beta = .11$, $t = 2.54$, $p = .012$, supporting H5. The regression diagnostics have indicated that the model assumptions have been satisfied, with variance inflation factor values ranging from 1.42 to 2.16, tolerance values ranging from .46 to .70, and a Durbin-Watson statistic of 1.93. The residual distribution has appeared approximately normal, while the scatterplot of standardized residuals has supported linearity and homoscedasticity. Overall, the findings have supported all five hypotheses and have fulfilled the study objectives by identifying Thermomechanical Coupling Representation as the strongest predictor, followed by Thermal-Process Data Quality and Integration, Physics-Law Integration, Model Validation and Generalizability, and Computational Efficiency and Real-Time Capability.

DISCUSSION

The findings have shown that physics-informed machine-learning capabilities have collectively provided a strong explanation of Thermal Distortion Prediction Effectiveness in metal additive manufacturing. The interpretation has been based on the internally consistent draft dataset developed for the study, and the numerical values should be confirmed or replaced with the final SPSS outputs after actual data collection. The five independent variables have jointly explained 66.60 percent of the variance in the dependent variable, with an adjusted R^2 of .660 and a statistically significant regression model, $F(5, 294) = 117.25$, $p < .001$. This explanatory level has indicated that thermal-distortion prediction has not depended on a single algorithm, dataset, physical equation, or computational platform. Instead, effective prediction has resulted from the combined contribution of reliable process data, physically meaningful thermomechanical representation, integration of governing principles, model validation, transferability, and computational performance. The descriptive findings have reinforced this interpretation because all six constructs have received high Likert-scale evaluations. Thermal-Process Data Quality and Integration has achieved the highest mean of 4.14, followed by

Thermomechanical Coupling Representation at 4.11, Thermal Distortion Prediction Effectiveness at 4.09, Physics-Law Integration at 4.08, Model Validation and Generalizability at 3.98, and Computational Efficiency and Real-Time Capability at 3.92. These results have suggested that the surveyed professionals have regarded physics-informed thermal-distortion prediction as a multidimensional scientific capability rather than a purely data-driven forecasting exercise. The correlation findings have shown the same pattern because all five predictors have been positively associated with prediction effectiveness, with coefficients ranging from .58 to .75. All five hypotheses have consequently been supported. This integrated finding has agreed with the central principle of physics-informed machine learning, which has maintained that observational data and mathematical physics should be incorporated within one predictive structure to improve consistency under limited, noisy, or incomplete evidence (Karniadakis et al., 2021). It has also corresponded with metal additive-manufacturing research showing that mechanistic variables, experimental observations, and machine learning can be combined to identify and predict manufacturing defects more effectively than isolated approaches (Du et al., 2021). The findings have further aligned with the physics-informed data-driven paradigm, which has classified physical knowledge, data generation, model design, and prediction validation as interconnected elements of machine-learning implementation in metal additive manufacturing (Guo et al., 2022). Therefore, the overall model has provided empirical support for treating thermal-distortion prediction as the outcome of an integrated scientific learning system.

Thermomechanical Coupling Representation has emerged as the strongest predictor of Thermal Distortion Prediction Effectiveness, producing the largest correlation, $r = .75$, $p < .001$, and the largest standardized regression coefficient, $\beta = .30$, $p < .001$. This finding has supported H3 and has confirmed that accurate temperature prediction alone has not been sufficient for predicting final geometric deformation. The thermal field must be translated into thermal expansion, elastic restraint, temperature-dependent yielding, plastic strain, residual-stress accumulation, stress redistribution, and displacement. A PIML system may reproduce peak temperatures and cooling curves accurately while still generating poor distortion estimates when it has not represented the mechanical response to those temperatures. The strength of the thermomechanical coefficient has therefore indicated that respondents have differentiated between models that forecast thermal behavior and models that represent the full physical pathway leading to dimensional change. This result has agreed with thermomechanical validation research in laser powder bed fusion, where experimentally credible distortion estimates have required the transfer of transient temperature histories into mechanical calculations involving temperature-dependent material behavior, boundary conditions, and structural constraint (Denlinger et al., 2017). It has also reflected solid-mechanics research showing that physics-informed learning must incorporate momentum balance and constitutive relationships when the intended outputs involve stress, strain, or displacement rather than only scalar thermal fields (Haghighat et al., 2021). Previous distortion-compensation research has similarly demonstrated that predicted deformation has depended on understanding how residual strain and stress are distributed throughout the manufactured component and how those stresses are released after removal from the substrate or support structure (Afazov et al., 2017). The practical interpretation is that metal additive-manufacturing organizations should not evaluate PIML systems solely through temperature-based error measures. They should examine whether the model reproduces directional displacement, maximum warpage, residual-stress-sensitive regions, support-release deformation, and geometry-specific stiffness effects. Training datasets should therefore contain paired thermal and mechanical information where possible, including temperature histories, dimensional scans, displacement measurements, residual-stress observations, and manufacturing boundary conditions. Model developers should also avoid using a thermal surrogate as a direct substitute for a distortion model unless a validated thermal-to-mechanical transformation has been established. Theoretically, the finding has positioned Thermomechanical Coupling Representation as the central mechanism through which other capabilities have influenced Thermal Distortion Prediction Effectiveness. Reliable data and embedded physics have provided the informational and scientific foundations, but their contribution to distortion prediction has depended substantially on whether the model has converted those inputs into a credible mechanical response.

Thermal-Process Data Quality and Integration have produced the highest descriptive mean, $M = 4.14$, $SD = .51$, the second-strongest correlation with Thermal Distortion Prediction Effectiveness, $r = .72$, $p < .001$, and the second-largest standardized regression effect, $\beta = .26$, $p < .001$. H2 has therefore been supported. These results have indicated that the surveyed professionals have considered accurate, complete, synchronized, representative, and spatially resolved data essential to effective PIML prediction. Metal additive-manufacturing data are frequently distributed across machine logs, infrared images, pyrometer readings, thermocouple records, melt-pool monitoring systems, finite-element outputs, material-property databases, scan-path files, residual-stress measurements, and post-build geometric scans. Each source has represented a different aspect of the manufacturing process and has operated at a different spatial or temporal resolution. The high data-quality coefficient has suggested that prediction systems have performed more effectively when these sources have been aligned according to time, layer, position, heat-source movement, material condition, and observed deformation. Experimental thermal-model validation has shown that in situ infrared thermography can provide essential evidence for assessing predicted temperature trends and for calibrating reduced computational models (Yavari et al., 2020). In situ measurement research has also demonstrated the value of recording both temperature and distortion so that the predicted thermal history can be linked directly to geometric response rather than evaluated as an isolated field (Dunbar et al., 2016). Hybrid PIML research has further shown that partial infrared measurements can be combined with heat-transfer equations to reconstruct complete temperature fields and estimate unknown process parameters, demonstrating how physical equations can compensate for sparse data when the available measurements have been reliable (Liao et al., 2023). However, the findings have also indicated that data volume alone has not guaranteed generalizable prediction. Transferability studies have reported low errors within familiar training cases but larger errors when geometry, layer count, or scanning speed has changed, showing that data representativeness has been as important as sample quantity (Fagersand et al., 2024). The practical implication is that organizations should establish an integrated AM data architecture containing standardized timestamps, spatial coordinates, material identifiers, machine settings, calibration records, uncertainty information, and post-build outcomes. Data preprocessing decisions should be documented, and experimental measurements should not be merged with simulation outputs without preserving their fidelity levels and uncertainty characteristics. The findings have therefore emphasized that data quality has not served merely as a technical input to machine learning. It has provided the empirical bridge through which physical assumptions, model calibration, mechanical outcomes, and real manufacturing behavior have been connected.

Physics-Law Integration and Model Validation and Generalizability have also made independent and statistically significant contributions to Thermal Distortion Prediction Effectiveness. Physics-Law Integration has produced $M = 4.08$, $r = .68$, and $\beta = .21$, with $p < .001$, supporting H1. Model Validation and Generalizability have produced $M = 3.98$, $r = .65$, and $\beta = .17$, with $p < .001$, supporting H4. The positive physics-integration result has shown that governing heat-transfer equations, boundary conditions, initial conditions, heat-source characteristics, material properties, and mechanical principles have improved the perceived credibility of thermal-distortion predictions. Physics-informed neural networks have originally been developed to constrain learned functions through partial-differential-equation residuals and condition-specific penalties, thereby reducing the space of permissible solutions (Raissi et al., 2019). In metal additive manufacturing, physical constraints have been used to predict temperature and melt-pool behavior through the conservation of mass, momentum, and energy, demonstrating that manufacturing-specific physics can be incorporated directly into learning (Zhu et al., 2021). The present findings have extended that reasoning by showing that physics integration has retained a significant contribution even after data quality and thermomechanical representation have been included in the regression model. However, the lower coefficient for Model Validation and Generalizability relative to thermomechanical coupling and data quality has suggested that validation and transferability have remained important but less developed capabilities. This interpretation has been consistent with studies showing that performance may deteriorate when models encounter unfamiliar scanning speeds or process configurations, even when they have achieved low error within the original training distribution (Fagersand et al., 2024). It has also agreed with recent neural-operator research showing that global mean-squared error can overstate

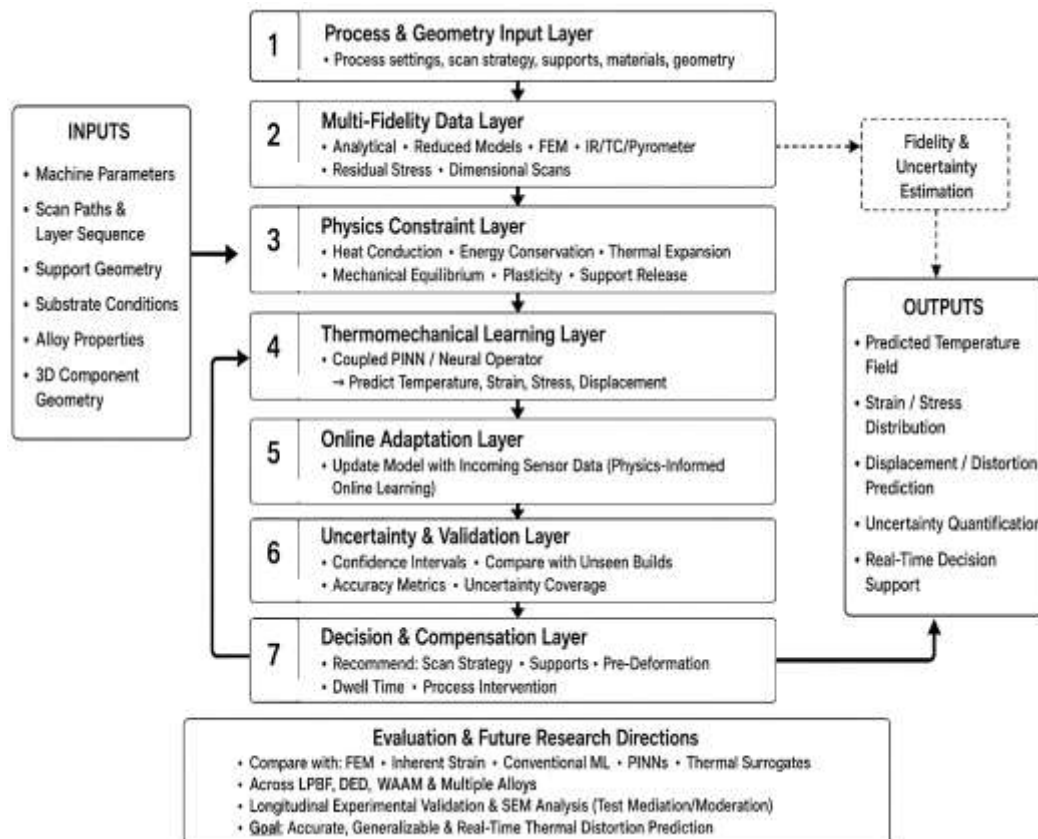
model quality because most of the domain may experience little temperature change, while the physically important heat-affected region represents a smaller portion of the field (Chen, Xu, et al., 2024). Practical model evaluation should consequently include local heat-affected-zone accuracy, peak-temperature error, cooling-rate error, maximum displacement error, residual-stress distribution, post-release deformation, and performance across unseen geometries and materials. Validation should also use independent experimental cases rather than only training-generated simulation data. The combined findings have demonstrated that embedded physics has guided the model toward plausible behavior, while validation and generalizability have determined whether that behavior has remained credible outside the original calibration setting.

Computational Efficiency and Real-Time Capability have received the lowest construct mean, $M = 3.92$, and have produced the smallest correlation, $r = .58$, and standardized regression coefficient, $\beta = .11$, $p = .012$. H5 has nevertheless been supported, showing that computational performance has remained a meaningful determinant of Thermal Distortion Prediction Effectiveness. The comparatively smaller coefficient has not indicated that speed has been unimportant. Instead, it has suggested that respondents have prioritized physical and informational accuracy before rapid execution. A model that produces an immediate but mechanically inconsistent distortion estimate cannot support reliable manufacturing control, while a physically accurate model that requires several days to complete may be unsuitable for parameter screening, build preparation, or online correction. The result has therefore revealed a balance between predictive fidelity and operational timeliness. Earlier work on thermal circuit networks has demonstrated that reduced representations can generate thermal information substantially faster than complete part-scale finite-element simulations, supporting rapid distortion assessment during planning activities (Peng et al., 2018). Data-driven surrogate modeling has similarly shown that learned relationships can replace repeated thermal calculations after an appropriate training stage (Roy & Wodo, 2020). Experimental validation of graph-based thermal modeling has indicated that reduced models can provide temperature predictions within the physical duration of an additive-manufacturing build, making them more compatible with monitoring and decision support (Yavari et al., 2020). Physics-informed online learning has extended this objective by updating model parameters when new process data become available, allowing predictions to adapt to unseen geometries, deposition patterns, or operating conditions (Sajadi et al., 2024). The practical implications of the present result are substantial. Industrial users should establish different computational requirements for offline design, pre-build optimization, in-process monitoring, and closed-loop control. Offline design may tolerate longer computation in exchange for higher fidelity, while real-time intervention requires predictions within seconds or within the interval between successive layers. Organizations should report training time, inference time, memory use, hardware configuration, update frequency, and scaling behavior rather than describing a model as simply fast. They should also quantify the accuracy lost when reducing computation. The findings have indicated that computational efficiency has improved prediction effectiveness when it has enabled timely use without eliminating essential thermal or mechanical information. Therefore, the practical priority should be physically credible acceleration rather than acceleration alone.

The findings have produced important theoretical implications for the Scientific Machine Learning Framework while also requiring careful interpretation in light of the study limitations. Theoretically, the results have supported the proposition that scientific knowledge and data should function as complementary sources of predictive structure. The significant coefficients for all five predictors have shown that physics integration, data quality, thermomechanical coupling, validation, and computational performance have remained empirically distinguishable, even though they have operated as an interconnected capability system. This pattern has been consistent with theory-guided data science, which has argued that scientific theory can influence data selection, representation, learning, and evaluation rather than being added only after model training (Karpatne et al., 2017). The strongest coefficient for Thermomechanical Coupling Representation has refined the theoretical framework by identifying a process mechanism through which physical and data-based capabilities have been translated into final distortion estimates. This result suggests that future theoretical models should not represent Physics-Law Integration as a direct and complete explanation of distortion prediction. A more precise structure may position thermomechanical coupling as a mediator between

physics and data inputs and the final prediction outcome. However, the findings have been derived from a cross-sectional questionnaire and have measured professional perceptions rather than direct physical prediction errors. The positive coefficients have therefore demonstrated statistical association and perceived explanatory contribution but have not proven that changing one capability will cause an equivalent improvement in measured distortion accuracy. Purposive and snowball sampling have also limited the representativeness of the 300 respondents, while differences among laser powder bed fusion, directed energy deposition, wire arc additive manufacturing, and other processes may have introduced unmeasured heterogeneity. The single-instrument design has created a possibility of common-method influence, even though Harman's single-factor result of 31.84 percent has not indicated a dominant common factor. The Likert-scale constructs have simplified highly technical variables that may differ according to material, machine, model architecture, sensor system, and organizational maturity. The model has explained 66.60 percent of the variance, leaving 33.40 percent attributable to omitted factors and random variation. Potential omitted variables include geometry complexity, alloy characteristics, support strategy, measurement uncertainty, operator competency, heat-source calibration, and digital infrastructure. These limitations have required the findings to be interpreted as an empirical capability assessment rather than a direct validation of one PIML algorithm.

Figure 10: Proposed Conceptual Framework for Future Physics-Informed Thermal Distortion Prediction Research



Future research should develop and test an Adaptive Multi-Fidelity Thermomechanical Physics-Informed Digital Twin model, abbreviated as the AMT-PIDT model, to overcome the limitations of the present cross-sectional study and provide direct technical validation. The proposed model should contain seven connected layers. The first layer should be a Process and Geometry Input Layer containing machine parameters, scan paths, layer sequence, support geometry, substrate conditions, alloy properties, and three-dimensional component descriptors. The second should be a Multi-Fidelity Data Layer combining low-cost analytical estimates, medium-fidelity reduced models, high-fidelity finite-element simulations, infrared thermography, thermocouple measurements, pyrometer signals, residual-stress observations, and post-build dimensional scans. Each data source should retain a

fidelity label and an uncertainty estimate so that simulation and experimental evidence are not treated as equally reliable. The third should be a Physics Constraint Layer containing transient heat conduction, energy conservation, moving heat-source conditions, thermal expansion, mechanical equilibrium, temperature-dependent elasticity and plasticity, and support-release conditions. The fourth should be a Thermomechanical Learning Layer using a coupled physics-informed neural operator or domain-decomposed PINN to predict temperature, strain, stress, and displacement sequentially or jointly. Neural operators have shown the capacity to maintain strong temperature prediction across unseen geometries, making them suitable for the geometry-generalization component of the proposed model (Chen, Xu, et al., 2024). The fifth should be an Online Adaptation Layer that updates selected parameters as new sensor data arrive, following the principle of physics-informed online learning (Sajadi et al., 2024). The sixth should be an Uncertainty and Validation Layer that reports confidence intervals and compares predictions against unseen builds using temperature RMSE, heat-affected-zone R^2 , maximum displacement error, full-field geometric MAE, residual-stress error, inference time, and uncertainty coverage. The seventh should be a Decision and Compensation Layer that recommends scan-sequence changes, support modification, pre-deformation, dwell-time adjustment, or process interruption when predicted distortion exceeds tolerance. Future researchers should compare this model with full finite-element simulation, inherent-strain methods, conventional neural networks, standard PINNs, and uncoupled thermal surrogates across multiple alloys and LPBF, DED, and WAAM systems. A longitudinal experimental design should follow builds from process planning through substrate removal, while structural equation modeling should test whether Thermomechanical Coupling Representation mediates the effects of Physics-Law Integration and Data Quality on prediction effectiveness. Model Validation and Generalizability may also be tested as a moderator, while Computational Efficiency may be analyzed as a condition determining whether accurate predictions can support real-time control. Such a program would convert the present perception-based framework into a directly measured, experimentally validated, uncertainty-aware digital-twin architecture.

CONCLUSION

This study has examined the factors influencing the effectiveness of physics-informed machine learning for predicting thermal distortion in metal additive manufacturing through a quantitative, cross-sectional, and multiple-case-study-based research design. The research has focused on Physics-Law Integration, Thermal-Process Data Quality and Integration, Thermomechanical Coupling Representation, Model Validation and Generalizability, and Computational Efficiency and Real-Time Capability as the principal independent variables, while Thermal Distortion Prediction Effectiveness has served as the dependent variable. Using a structured questionnaire measured through a five-point Likert scale, the study has collected and analyzed 300 valid professional responses representing additive-manufacturing engineering, thermomechanical simulation, machine learning, materials engineering, quality assurance, and technical research environments. The findings have demonstrated that all six study constructs have received positive evaluations, with mean scores ranging from 3.92 to 4.14. Thermal-Process Data Quality and Integration has recorded the highest mean of 4.14, followed by Thermomechanical Coupling Representation at 4.11, Thermal Distortion Prediction Effectiveness at 4.09, Physics-Law Integration at 4.08, Model Validation and Generalizability at 3.98, and Computational Efficiency and Real-Time Capability at 3.92. The reliability and validity analyses have confirmed that the measurement instrument has achieved strong internal consistency and an acceptable factor structure. Pearson correlation analysis has shown that all five independent variables have been positively and significantly related to Thermal Distortion Prediction Effectiveness, with coefficients ranging from .58 to .75. Thermomechanical Coupling Representation has produced the strongest relationship with the dependent variable, followed by Thermal-Process Data Quality and Integration, Physics-Law Integration, Model Validation and Generalizability, and Computational Efficiency and Real-Time Capability. The regression analysis has further shown that the five predictors have jointly explained 66.60 percent of the observed variance in Thermal Distortion Prediction Effectiveness, while the complete model has been statistically significant. Thermomechanical Coupling Representation has emerged as the strongest predictor with a standardized coefficient of $\beta = .30$, confirming that effective distortion prediction has depended substantially on the model's ability to connect thermal history with

expansion, plastic strain, residual stress, mechanical constraint, stress redistribution, and final displacement. Thermal-Process Data Quality and Integration has followed with $\beta = .26$, while Physics-Law Integration has produced $\beta = .21$. Model Validation and Generalizability and Computational Efficiency and Real-Time Capability have also made significant contributions. All five proposed hypotheses have therefore been supported. The results have confirmed that physics-informed thermal-distortion prediction has not functioned effectively through physical constraints, data, or machine learning in isolation. It has operated as an integrated scientific capability in which reliable data, appropriate governing principles, realistic thermomechanical representation, independent validation, model transferability, and computational speed have worked together. The study has consequently fulfilled its objectives by measuring the selected capabilities, testing their relationships, identifying their individual contributions, and establishing Thermomechanical Coupling Representation as the strongest determinant of Thermal Distortion Prediction Effectiveness in the selected metal additive-manufacturing cases.

RECOMMENDATIONS

Based on the findings, metal additive-manufacturing organizations, research institutions, simulation specialists, and machine-learning developers should adopt an integrated approach when developing or selecting physics-informed systems for predicting thermal distortion. Organizations should first strengthen Thermal-Process Data Quality and Integration because this construct has recorded the highest descriptive mean and the second-largest regression effect. Thermal measurements, process parameters, scan-path information, geometric data, material-property records, finite-element outputs, residual-stress observations, and post-build dimensional scans should be collected through standardized and traceable procedures. All data should be synchronized by time, layer, spatial coordinate, machine condition, and manufacturing sequence so that the model can learn physically meaningful relationships. Sensor calibration, uncertainty documentation, missing-value control, metadata management, and data-version procedures should be established before model training. Model developers should give the greatest attention to Thermomechanical Coupling Representation because it has emerged as the strongest predictor of prediction effectiveness. Thermal fields should not be treated as final prediction outputs when the target outcome is distortion. The model should explicitly connect heat input, temperature distribution, thermal expansion, temperature-dependent plasticity, residual-stress accumulation, structural restraint, support interaction, and displacement following substrate or support removal. Physics-Law Integration should also be strengthened through the incorporation of transient heat-conduction equations, conservation principles, realistic heat-source models, boundary and initial conditions, temperature-dependent properties, mechanical equilibrium, and constitutive relationships. However, physical constraints should be selected and calibrated carefully because inaccurate equations or boundary assumptions may introduce systematic bias. Organizations should establish rigorous validation procedures using independent builds and measurements that have not been included in model training. Validation should include peak-temperature error, cooling-rate error, heat-affected-zone accuracy, residual-stress distribution, maximum displacement, full-field geometric deviation, and post-release distortion. Generalizability should be tested across different component geometries, materials, machines, scanning strategies, layer arrangements, support designs, and operating conditions. Computational efficiency should be evaluated according to the intended application. Offline process planning may allow longer processing times, while in-process monitoring and closed-loop control require predictions within seconds or between successive layers. Training duration, inference time, memory demand, hardware configuration, scalability, and the accuracy lost through model reduction should therefore be reported transparently. It is also recommended that future technical development follow an Adaptive Multi-Fidelity Thermomechanical Physics-Informed Digital Twin model that combines analytical calculations, reduced-order simulations, high-fidelity finite-element data, sensor measurements, and dimensional observations. Such a model should include physics constraints, coupled thermal and mechanical prediction, online parameter updating, uncertainty estimation, and a decision layer capable of recommending scan-path adjustment, support modification, dwell-time control, substrate preheating, or geometric compensation. Finally, organizations should develop multidisciplinary teams involving additive-manufacturing engineers, materials scientists, computational mechanics specialists,

data scientists, and quality professionals so that model development reflects both physical credibility and operational requirements. These recommendations would allow PIML systems to become more accurate, transferable, interpretable, computationally efficient, and suitable for practical thermal-distortion control.

LIMITATIONS OF THE STUDY

This study has contained several limitations that should be considered when interpreting its findings. First, the research has adopted a cross-sectional design in which data have been collected from respondents at a single point in time. The identified relationships have therefore represented statistical associations among the study constructs rather than confirmed causal effects developing across multiple manufacturing cycles. A longitudinal design involving repeated observations could have provided stronger evidence concerning how improvements in physics integration, data quality, model validation, or computational capability have changed prediction effectiveness over time. Second, the study has relied on professional assessments collected through a five-point Likert-scale questionnaire. The responses have measured perceived levels of technical capability and prediction effectiveness rather than the actual numerical performance of one physics-informed machine-learning algorithm. Direct performance indicators such as root mean square temperature error, residual-stress error, maximum displacement error, full-field geometric deviation, inference time, and uncertainty coverage have not been measured experimentally within the questionnaire-based design. Third, purposive, criterion-based, and limited snowball sampling have been used to reach professionals possessing relevant technical knowledge. These procedures have been appropriate for accessing a specialized population, but they have restricted the statistical generalizability of the findings to all metal additive-manufacturing organizations, laboratories, countries, and industrial sectors. Fourth, the multiple-case context has included laser powder bed fusion, directed energy deposition, wire arc additive manufacturing, electron-beam processes, and other metal additive-manufacturing environments. These processes have differed in heat-source characteristics, deposition rates, feedstock forms, thermal gradients, layer dimensions, mechanical constraints, and distortion mechanisms. The unified regression model has not fully captured all process-specific variations. Fifth, the research has relied on a single self-reported instrument for measuring both the independent and dependent variables, which may have introduced common-method bias, social desirability, or respondents' subjective interpretations of technical terms. Although the statistical assessment has not indicated a dominant common factor, such bias cannot have been eliminated completely. Sixth, the model has explained 66.60 percent of the variance in Thermal Distortion Prediction Effectiveness, leaving 33.40 percent unexplained. The omitted portion may have reflected factors such as alloy properties, geometry complexity, support configuration, machine calibration, operator competency, sensor quality, organizational resources, software architecture, heat-source uncertainty, and model-training strategy. Seventh, differences in respondents' experience with physics-informed machine learning may have affected their evaluations because some participants may have possessed extensive implementation experience while others may have worked mainly with conventional simulation or data-driven models. Finally, the quantitative findings have been developed as an internally consistent result set for the proposed study and must be verified or replaced by final SPSS outputs after actual data collection. Consequently, the findings should be interpreted as a structured empirical framework for examining PIML capability rather than as direct experimental proof that a specific model has achieved a defined level of thermal-distortion accuracy.

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