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Physics-Informed Machine Learning for Long-Term Polymer Performance Prediction from Extrusion Parameters, Material Properties, and Creep Data

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Abstract

Reliable prediction of long-term polymer performance remains difficult because extrusion conditions, intrinsic material properties, and time-dependent creep behavior are often analyzed separately, while purely data-driven models may achieve statistical fit without preserving physical meaning. This study aimed to develop and quantitatively evaluate a physics-informed machine-learning framework that integrates extrusion parameters, material properties, creep characteristics, and physically derived features for predicting long-term polymer performance. A quantitative, cross-sectional, multiple-case-based design was applied to 177 technically comparable polymer extrusion cases, including HDPE, polypropylene, LDPE, thermoplastic polyurethane, PMMA, and other thermoplastics, supported by assessments from engineers and technical specialists. Key variables comprised Extrusion Parameters, Material Properties, Creep Data, Physics-Informed Features, and Long-Term Polymer Performance. Data analysis employed descriptive statistics, Cronbach's alpha, KMO and Bartlett tests, Pearson correlation, hierarchical multiple regression, regression diagnostics, R-squared, adjusted R-squared, change in R-squared, F-change, standardized beta coefficients, RMSE, and MAE. Findings showed that long-term polymer performance averaged 4.07 ± 0.56, while correlations with performance were significant for extrusion parameters ($r = 0.58$), material properties ($r = 0.67$), creep characteristics ($r = 0.71$), and physics-informed features ($r = 0.74$), all $p < .001$. The final physics-informed model explained 69.8% of performance variance, with adjusted R-squared = 0.684 and $F = 42.86$, $p < .001$. Physics-informed features were the strongest predictor ($\beta = 0.36$, $p < .001$), and their inclusion added 9.1% explained variance. Predictive error also improved, with RMSE decreasing from 0.49 to 0.39 and MAE from 0.38 to 0.30. These results indicate that physics-informed integration can improve interpretability, predictive reliability, process optimization, durability assessment, and engineering decision support for long-term polymer applications, while maintaining explicit links between processing history, viscoelastic behavior, material state, and service-oriented performance outcomes across cases.

Keywords: *Physics-Informed Machine Learning; Polymer Extrusion; Long-Term Polymer Performance; Creep Characteristics; Hierarchical Regression Modeling*

INTRODUCTION

Polymers are macromolecular materials composed of repeating molecular units whose mechanical, thermal, rheological, and time-dependent properties arise from interactions among molecular architecture, morphology, processing history, and environmental conditions. In engineering applications, long-term polymer performance refers to the ability of a polymeric component to retain its required mechanical integrity, dimensional stability, stiffness, deformation resistance, and functional properties during sustained exposure to load, temperature, and service time. Extrusion is a continuous polymer-processing operation in which a polymer is transported, heated, melted, mixed, subjected to shear and pressure, and forced through a die to obtain a controlled product geometry. Internationally, extrusion supports the production of pipes, films, sheets, cables, profiles, packaging materials, structural products, medical products, and compounded materials, making control of the process-property relationship important across manufacturing sectors (Hyvarinen et al., 2020; Wilczynski et al., 2019). Recent Advances in Reactive Extrusion Processing (pp. 447-470) illustrates that extrusion can simultaneously generate thermal, mechanical, mixing, and chemical effects that modify the state and properties of polymer systems during processing (Raquez et al., 2008). Extrusion efficiency itself is associated not merely with throughput but with energy consumption, pressure stability, homogenization, and the thermal and mechanical quality of the extrudate (Sikora, 2008). On the High-Density Polyethylene Extrusion (pp. 173-184) demonstrates that polymer flow in industrial extrusion is non-Newtonian and non-isothermal and that pressure, temperature, flow distribution, and viscous heating interact inside the die, establishing a direct physical basis for treating extrusion conditions as explanatory variables rather than isolated machine settings (Mamalis et al., 2010). Screw speed also alters the thermomechanical environment imposed on polymer-based materials and can modify the resulting material response, which reinforces the need to relate processing conditions to measurable performance characteristics rather than studying processing and properties separately (Chevali & Ulven, 2012).

Process optimization studies similarly identify screw configuration, screw speed, temperature, feed conditions, residence behavior, and die-related variables as interacting determinants of polymer-processing outcomes (Gaspar-Cunha et al., 2022; Thiry et al., 2015). These relationships make extrusion parameters, intrinsic material characteristics, and subsequently measured mechanical behavior parts of one interconnected physical system rather than independent sources of information. The long-term response of an extruded polymer cannot be characterized adequately from instantaneous strength or stiffness alone because polymeric solids exhibit viscoelasticity, meaning that their deformation contains both recoverable elastic and time-dependent viscous components. Creep is the progressive increase in strain under sustained stress, and it provides a central measure of how a polymer evolves mechanically during prolonged loading. The magnitude and rate of creep depend on stress level, temperature, molecular mobility, morphology, material composition, physical aging, and prior processing conditions. Extrudate Swell of Linear and Branched Polyethylenes (pp. 12-24) demonstrates that nonlinear viscoelastic characteristics, including shear viscosity, extensional viscosity, and normal-stress behavior, govern polymer response during extrusion and that constitutive representation of the material is necessary for accurate process prediction (Ganvir et al., 2011). Such observations connect processing rheology with the time-dependent constitutive behavior that subsequently controls dimensional and mechanical stability. Long-Term Creep Assessment of Viscoelastic Polymer (pp. 571-578) showed that short-term creep measurements obtained at different stresses and temperatures can be shifted into a unified master curve and used to represent behavior over much longer periods, while also showing that temperature and stress effects are coupled in nonlinear viscoelastic conditions (Luo et al., 2012).

Time-temperature superposition similarly allows creep compliance measured over experimentally manageable durations to represent longer response periods by shifting observations along the time domain according to temperature-dependent factors (Krauklis et al., 2019). Thermoplastic characterization has further established that time-temperature superposition can represent viscoelastic and viscoplastic behavior over broad temperature and strain-rate conditions with substantially reduced experimental requirements (Dorleans et al., 2021). Molecular-dynamics analysis of polypropylene has also connected the operation of time-temperature superposition to free volume and temperature-

dependent molecular mobility, providing a microscopic basis for the shift behavior used in long-term polymer characterization (Yuan & Sakai, 2024). Recent creep modeling of thermoplastic and thermosetting polymers has shown that master-curve parameters can also be related to composition, confirming that long-term mechanical response contains structured information about material formulation rather than only elapsed loading time (Rony & Md, 2026; Virag & Molnar, 2024).

The difficulty of long-term prediction increases because extrusion parameters, material descriptors, and creep variables operate at different physical scales and often interact nonlinearly. A change in processing temperature can alter viscosity and thermal history, while screw speed and residence conditions influence shear exposure and mixing; these process histories can subsequently affect structure-sensitive properties that govern creep resistance and mechanical retention. Conventional modeling therefore faces the problem of connecting process information with material characteristics and time-dependent response without reducing the system to a single empirical correlation. Polymer informatics has provided a data-centered route for describing such multidimensional relationships. Polymer Genome: A Data-Powered Polymer Informatics Platform (pp. 17575-17585) demonstrated that hierarchical polymer representations combined with machine-learning surrogate models can map chemical information to multiple polymer properties across diverse material classes (Kim et al., 2018; Kanti, 2026). Machine-learning-assisted molecular design has similarly shown that quantitative structure-property relationships can be learned from relatively limited polymer datasets when physically meaningful material descriptions are supplied to the algorithm (Wu et al., 2019).

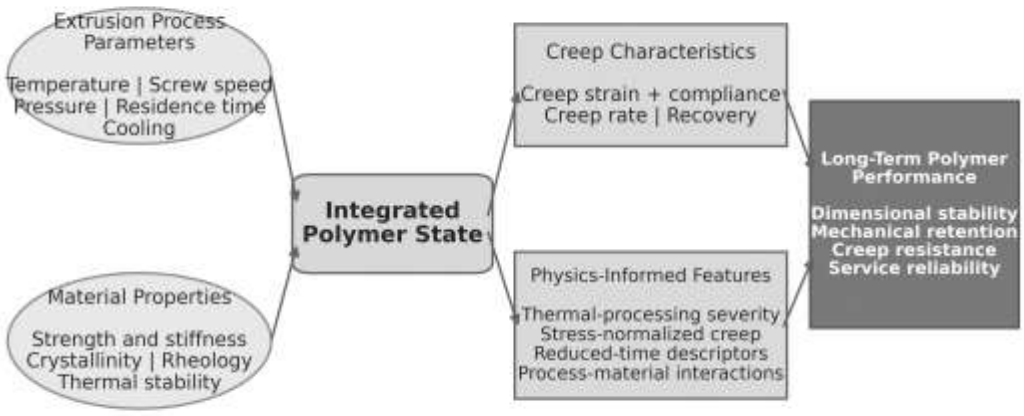
Broader polymer-design research has formalized the use of descriptors, supervised learning, surrogate modeling, and inverse design for organizing complex polymer composition-property spaces (Chen et al., 2020; Shamima, 2026). Property-specific models have successfully represented frequency-dependent dielectric response across extremely wide frequency ranges, illustrating that polymer behavior can be learned as a function of both material representation and an external physical variable (Chen et al., 2020; Pervaz, 2026). The Polymer Genome framework has further demonstrated machine-learning prediction across numerous polymer-property categories using experimental and computational data combined within curated representations (Kaium, 2026; Tran et al., 2020). Multi-task learning has addressed data scarcity by transferring information among related polymer-property prediction tasks, a particularly relevant feature when engineering datasets contain many descriptors but comparatively limited numbers of qualified cases (Kuenneth et al., 2021; Mashiat, 2026). Reviews of polymer informatics have therefore identified data curation, polymer representation, processing information, property descriptors, and model validation as central components of reliable property prediction rather than treating algorithm choice as the sole determinant of performance (Andraju et al., 2022; Chen et al., 2021).

Machine learning becomes especially relevant for long-term polymer characterization when measured creep behavior is treated as a source of predictive information rather than as a separate end-of-life test. Comparative Study of Machine Learning Approaches for Predicting Creep Behavior of Polyurethane Elastomer directly incorporated creep time, temperature, stress, and material hardness into multilayer perceptron, random-forest, and support-vector-regression models, establishing that long-duration viscoelastic response can be represented through multivariable supervised learning rather than through time alone (Mashfiqur, 2026; Yang et al., 2021). This type of formulation aligns closely with the need to integrate extrusion conditions with material and creep descriptors because each group of variables contributes information about a different stage in the process-property-performance chain. Data-driven polymer models, however, can learn statistical regularities that do not necessarily represent physical causation, particularly when samples are limited, correlated, or collected from repeated experimental groups. Prevention of Leakage in Machine Learning Prediction for Polymer Composite Properties (pp. 3621-3629) demonstrated that conventional random data splitting can overestimate predictive performance when related experimental observations are allowed to appear in both training and testing subsets, highlighting the importance of case-aware validation in materials prediction (Khalid, 2026; Shimakawa et al., 2024). Machine-learning property prediction also depends strongly on the mathematical representation of polymers and the dimensionality of the input space, because redundant or weak descriptors can obscure relationships between material state and observed response (Jannatul, 2026; Mysona et al., 2024). The distinction between correlation and physical

consistency becomes particularly important in creep prediction, where stress, temperature, reduced time, relaxation processes, and rheological state are connected through established viscoelastic principles. Data-driven models can represent such interactions numerically, while constitutive knowledge supplies information about which transformations and descriptors possess physical meaning. This establishes a methodological basis for combining raw extrusion variables, measured material properties, creep observations, and derived viscoelastic quantities in a single predictive architecture rather than relying only on an unconstrained black-box learner (Jahanara, 2026; Shimakawa et al., 2024; Yang et al., 2021).

Physics-informed machine learning provides a structured means of integrating such physical knowledge with statistical learning. In this context, physics-informed machine learning refers to computational learning in which physical laws, constitutive relationships, mechanistic descriptors, conservation principles, or physically derived variables are embedded within model inputs, architecture, objectives, or constraints so that prediction is informed by both observations and established system behavior. Physics-Informed Machine Learning (pp. 422-440) characterizes this approach as an integration of data and mathematical physics that can address complex systems where purely numerical simulation or purely data-driven learning is individually insufficient (Ahmed, 2026; Karniadakis et al., 2021). For polymer performance prediction, the relevant physical information can include temperature-dependent shift factors, creep coefficients, reduced time, stress normalization, viscosity-related descriptors, thermal-processing severity, specific mechanical energy, and process-material interaction quantities. Physics-informed property modeling has already shown that physically derived information can improve representation of viscosity-related behavior when combined with machine-learning models (Chew et al., 2024; Feroz, 2025). Physics-Informed Machine Learning Enabled Virtual Experimentation for 3D Printed Thermoplastic (pp. 6028-6039) provides a polymer-specific example in which physics-informed descriptors and dimensionality reduction were incorporated into a neural predictive system for thermoplastic stress-strain response, achieving strong agreement between predicted and experimentally measured behavior (Chen et al., 2024; Chandra, 2025). Polymer-processing modeling has independently established that extrusion prediction requires simultaneous consideration of solid transport, melting, melt flow, screw-die interaction, temperature, pressure, residence conditions, and material rheology, reinforcing the value of combining mechanistic variables rather than using isolated settings (Hyvarinen et al., 2020; Pervaz, 2025; Wilczynski et al., 2019). Within the present research context, long-term polymer performance is therefore treated as a quantitatively observable response generated by an interconnected set of extrusion parameters, material properties, creep characteristics, and physics-informed derived features. The analytical focus is placed on measuring their descriptive patterns, pairwise relationships, incremental regression contributions, and predictive behavior within a cross-sectional case-based dataset, with physics-derived information retained as an explicit component of the model rather than hidden within an undifferentiated statistical input space (Chen et al., 2024; Karniadakis et al., 2021; Kaium, 2025).

Figure 1: Integrated Overview of Physics-Informed Long-Term Polymer Performance Prediction



1.1 Background of the Study

Polymer extrusion is one of the most important continuous manufacturing processes used to produce pipes, films, sheets, profiles, insulation materials, packaging components, structural products, and numerous engineering parts. The final performance of an extruded polymer does not depend on material composition alone because the polymer experiences a complex combination of temperature, shear, pressure, residence time, flow history, cooling, and deformation during processing. These conditions can alter molecular orientation, crystallinity, thermal stability, viscosity, residual stress, density, and mechanical properties, which subsequently influence the ability of the material to maintain dimensional and structural integrity over extended service periods. Long-term polymer performance is particularly difficult to evaluate because polymers exhibit viscoelastic behavior and therefore respond to sustained loading in a time-dependent manner. Creep deformation can continue even when the applied stress remains constant, and its progression can be accelerated by temperature, stress level, material aging, morphological changes, and unfavorable processing conditions. Conventional characterization methods usually examine extrusion conditions, short-term mechanical properties, or creep behavior independently, which limits their ability to explain how processing history, intrinsic material characteristics, and time-dependent deformation interact to determine long-term performance. Machine learning provides a quantitative means of analyzing multidimensional relationships among these variables, but purely data-driven models may identify statistical patterns without incorporating the physical mechanisms governing polymer deformation. This limitation is especially relevant when the number of available engineering cases is comparatively small or when predictions must extend beyond directly observed operating conditions. Physics-informed machine learning offers a more structured approach by integrating measured data with physically meaningful descriptors derived from polymer rheology, viscoelasticity, thermal exposure, creep behavior, and process-material interactions. The present study has therefore been developed around a quantitative, cross-sectional, case-study-based framework that integrates extrusion parameters, material properties, creep data, and physics-informed features within a unified predictive structure. The study has applied descriptive statistics, Pearson correlation analysis, and Physics-Informed Hybrid Hierarchical Regression Modeling to examine how different groups of variables contribute to long-term polymer performance. A five-point Likert scale has additionally been used to quantify case-specific engineering assessments concerning process stability, material consistency, creep resistance, and performance reliability. Through this integrated structure, the research has treated long-term polymer behavior as the outcome of interconnected processing, material, rheological, and time-dependent mechanisms rather than as the result of a single isolated factor.

1.2 Problem Statement

Reliable prediction of long-term polymer performance remains a significant technical challenge because extrusion processing, material characteristics, and time-dependent creep behavior are often evaluated as separate aspects of polymer engineering. Industrial extrusion systems generate complex thermal and mechanical histories through variations in melt temperature, barrel temperature, screw speed, pressure, residence time, throughput, shear conditions, and cooling rate. These processing conditions can substantially influence polymer morphology and mechanical behavior, yet their effects may not become fully visible during conventional short-term quality-control testing. A polymer component may satisfy initial strength, stiffness, or dimensional requirements while gradually developing excessive creep deformation or property loss during prolonged service. Existing empirical models can estimate creep under specified conditions, while conventional machine-learning models can identify multivariable statistical relationships, but each approach has limitations when used independently. Empirical constitutive models may simplify complex process-property interactions, whereas unconstrained machine-learning models may generate accurate statistical fits without ensuring that their relationships remain physically meaningful. Another problem concerns the separation of manufacturing information from subsequent material-performance data. Extrusion parameters are often analyzed independently from tensile, thermal, rheological, or creep properties, making it difficult to quantify how processing history contributes to long-term behavior. Data scarcity, heterogeneity among polymer grades, inconsistent creep-test conditions, correlated predictors, and limited long-duration observations further complicate predictive modeling. In addition, studies that apply machine learning to polymer properties frequently focus on molecular descriptors or isolated material properties rather than integrating manufacturing conditions, material characteristics, creep response, and physically derived variables within one interpretable framework. Consequently, there is a methodological gap in developing a statistically testable and physically grounded model that can determine the individual and combined effects of extrusion parameters, material properties, creep characteristics, and physics-informed features on long-term polymer performance. The present research has addressed this problem by developing a Physics-Informed Hybrid Hierarchical Regression Model capable of comparing conventional data-driven prediction with an augmented model that incorporates physically meaningful descriptors derived from extrusion and viscoelastic behavior.

1.3 Purpose and Objectives of the Study

The primary purpose of this study has been to develop and quantitatively evaluate a physics-informed machine-learning framework for predicting long-term polymer performance by integrating extrusion-process parameters, material properties, creep-response characteristics, and physically derived engineering features within a single analytical model. The research has been designed to determine whether long-term polymer behavior can be explained more effectively when manufacturing information and viscoelastic response are analyzed jointly rather than independently. Specifically, the study has sought to characterize the statistical distribution and variability of extrusion parameters, material properties, creep characteristics, physics-informed features, and long-term performance indicators across selected polymer-processing cases. It has further aimed to examine the strength and direction of relationships among these variables using Pearson correlation analysis and to determine the independent contribution of major predictor groups through hierarchical multiple regression. A central objective has been to develop physics-informed features that represent important mechanisms associated with polymer processing and creep, including thermal-processing severity, stress-normalized deformation, creep coefficients, time-dependent response parameters, and relevant process-material interaction terms. The study has also aimed to compare a conventional model based on directly measured extrusion, material, and creep variables with an augmented physics-informed model in order to determine whether the addition of physically meaningful features produces a measurable increase in explanatory and predictive capability. Another objective has been to identify the most influential predictors of long-term polymer performance and determine whether extrusion conditions, material characteristics, and creep response provide distinct or overlapping contributions. The research has also sought to evaluate the statistical adequacy of the proposed predictive model through reliability testing, construct assessment, regression diagnostics, coefficient interpretation, R-

squared measures, adjusted R-squared values, incremental changes in explained variance, and prediction-error measures. Through these objectives, the study has established a structured quantitative framework for examining the full process-property-creep-performance pathway in extruded polymer systems.

1.4 Research Hypotheses

The hypotheses of this study have been formulated to test the proposed relationships among extrusion-process parameters, material properties, creep characteristics, physics-informed features, and long-term polymer performance within the Physics-Informed Hybrid Hierarchical Regression framework. The first hypothesis, H1, has stated that extrusion-process parameters have a statistically significant effect on long-term polymer performance. The second hypothesis, H2, has stated that material properties have a statistically significant effect on long-term polymer performance. The third hypothesis, H3, has stated that creep characteristics have a statistically significant effect on long-term polymer performance, recognizing creep as a direct representation of time-dependent deformation under sustained loading. The fourth hypothesis, H4, has stated that physics-informed features have a statistically significant effect on long-term polymer performance. These features have included physically derived quantities representing thermal exposure, stress-normalized response, creep-law parameters, reduced-time characteristics, and processing-material interactions. The fifth hypothesis, H5, has stated that extrusion parameters, material properties, creep characteristics, and physics-informed features jointly provide a statistically significant prediction of long-term polymer performance. This hypothesis has evaluated the overall integrated predictive model rather than examining individual variable groups separately. The sixth hypothesis, H6, has stated that incorporating physics-informed features significantly improves the predictive capability of the model compared with a conventional data-driven model containing only directly measured extrusion, material, and creep variables. The corresponding null hypotheses have stated that no statistically significant effects or improvements exist for the respective relationships. These hypotheses have provided the statistical structure required to evaluate both the explanatory contribution of individual predictor domains and the added value of physics-informed modeling.

1.5 Significance of the Research

i. Significance for polymer-processing engineering: The study has provided a structured method for examining how extrusion conditions influence long-term polymer performance rather than limiting process evaluation to immediate production quality. By integrating temperature, screw speed, pressure, residence conditions, material characteristics, and creep behavior, the research has offered a more comprehensive representation of process-dependent performance.

ii. Significance for materials characterization: The research has connected conventional material-property measurements with long-term viscoelastic response. This has allowed tensile, thermal, rheological, and structural characteristics to be evaluated alongside creep-related variables rather than as isolated indicators of quality.

iii. Significance for creep and durability assessment: The study has treated creep data as a central predictive component of long-term behavior. Physically meaningful creep parameters have therefore been incorporated directly into a broader statistical framework for evaluating dimensional stability, deformation resistance, and service reliability.

iv. Significance for physics-informed machine learning: The research has provided an interpretable alternative to purely black-box prediction by combining statistical learning with variables derived from established polymer-processing and viscoelastic principles. The comparison between conventional and physics-informed models has enabled the added contribution of physical information to be measured quantitatively.

v. Significance for industrial quality control: The proposed framework has supported more informed interpretation of production data by linking processing conditions with material and creep behavior. This can strengthen identification of unfavorable combinations of process settings and material characteristics associated with reduced long-term performance.

vi. Significance for research methodology: The study has developed a consistent analytical structure that combines a quantitative cross-sectional multiple-case design, purposive sampling, five-point Likert assessment, descriptive statistics, Pearson correlation, regression diagnostics, hierarchical

multiple regression, and predictive-error evaluation. This design has enabled explanatory statistical testing and predictive modeling within the same research framework.

vii. Significance for polymer-performance research: The study has addressed fragmentation between process analysis, material characterization, creep modeling, and machine-learning prediction by placing these components within a single process-property-performance model. This has made it possible to evaluate both individual effects and combined predictive relationships across the complete polymer-performance pathway.

LITERATURE REVIEW

The literature concerning long-term polymer performance spans several closely connected fields, including polymer extrusion, rheology, material characterization, viscoelasticity, creep mechanics, constitutive modeling, machine learning, and physics-informed predictive analysis. These research areas collectively explain how processing conditions influence the internal state of polymeric materials and how this state subsequently governs mechanical response over time. Extrusion represents a particularly complex manufacturing environment because temperature, pressure, screw speed, shear, residence time, cooling conditions, and throughput interact continuously during material transport, melting, homogenization, and shaping. The effects of these processing variables can be reflected in viscosity, morphology, molecular orientation, crystallinity, residual stress, and mechanical characteristics. Long-term behavior introduces an additional level of complexity because polymeric materials are viscoelastic and therefore exhibit deformation that depends on stress magnitude, temperature, loading duration, material structure, and previous processing history. Creep characterization has consequently become an important approach for quantifying progressive deformation and estimating durability under sustained loading. Conventional constitutive and empirical models provide physically meaningful representations of creep, while time-temperature superposition and related methods extend experimental observations across broader time scales. Machine-learning methods introduce the capacity to analyze large numbers of interacting descriptors simultaneously and identify nonlinear relationships that may be difficult to represent through conventional equations alone. Physics-informed machine learning connects these approaches by incorporating established physical knowledge into data-based predictive modeling. Within the context of this study, the literature has therefore been organized around six interconnected areas: extrusion-process effects on polymer behavior, material properties governing long-term performance, creep and viscoelastic deformation, physics-informed machine learning and hybrid predictive modeling, Viscoelasticity Theory as the theoretical framework, and the conceptual framework linking extrusion parameters, material characteristics, creep data, physics-informed features, and long-term polymer performance.

2.1 Polymer Extrusion Parameters and Process-Induced Material Behavior

Polymer extrusion is governed by a tightly coupled set of thermal, mechanical, rheological, and transport phenomena in which operating conditions determine the state of the polymer melt and influence the properties retained after solidification. Barrel temperature, screw rotational speed, feed rate, throughput, pressure development, screw geometry, residence time, and cooling conditions cannot be treated as completely independent parameters because changing one condition can alter several aspects of polymer behavior simultaneously. Temperature directly influences melt viscosity and molecular mobility, whereas screw rotation controls material conveying, shear generation, mixing intensity, viscous dissipation, and the time available for melting and homogenization. Residence time is particularly important because the duration of thermal and mechanical exposure determines how long polymer chains remain under processing conditions capable of inducing structural rearrangement or degradation. Residence Time Distribution of a Pharmaceutical Grade Polymer Melt in a Single Screw Extrusion Process (pp. 809-816) experimentally demonstrated that increases in either screw speed or processing temperature shortened residence time, although the two operating parameters affected polymer flow through different mechanisms. The study also showed that residence behavior could not be represented solely by nominal throughput because regions characterized by plug flow, mixing, and relatively stagnant material contributed differently to the overall residence-time distribution. These findings are relevant to long-term polymer-performance prediction because residence time represents

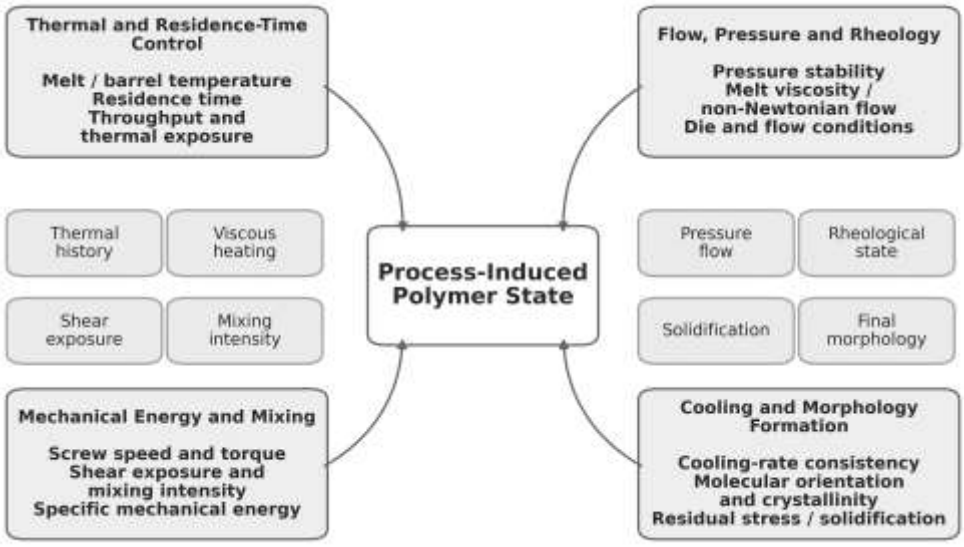
a link between externally selected extrusion settings and the cumulative thermal history experienced by the material. A short residence period may restrict thermal exposure while simultaneously increasing shear intensity when it is produced by higher screw rotation, whereas a prolonged residence period can increase the opportunity for thermal oxidation, molecular-weight alteration, or morphological development. Consequently, two extrusion cases with similar nominal melt temperatures may still produce different polymer states when screw speed, filling degree, and residence characteristics differ. Within a physics-informed framework, residence time therefore functions not only as an independent process variable but also as a physically interpretable descriptor of the exposure pathway through which temperature, flow, and mechanical deformation can influence subsequent material performance. This supports the use of case-specific extrusion histories when relating processing parameters to creep resistance and long-term service behavior rather than relying exclusively on machine set points (Ashik & Shabbir, 2022; Nikitine et al., 2009).

Mechanical energy transfer constitutes another central mechanism connecting extrusion conditions with the internal state and resulting properties of polymeric materials. During screw rotation, mechanical work is transferred to the polymer through drag, deformation, mixing, and shear, while part of this energy is converted into heat through viscous dissipation. The amount of energy imposed per unit mass can therefore capture interactions among screw speed, torque, throughput, polymer viscosity, and screw configuration more effectively than any of these operating variables considered individually. The Importance of Specific Mechanical Energy During Twin Screw Extrusion of Organoclay Based Polypropylene Nanocomposites (pp. 7-14) demonstrated that specific mechanical energy could summarize the combined effects of screw rotation speed, feed rate, and barrel temperature on dispersion development during twin-screw extrusion. The reported morphological observations showed that microscale dispersion occurred strongly during melting, while continuing exfoliation developed through kneading sections, indicating that the structural state of an extruded polymer system reflects cumulative processing history rather than conditions at the die alone. The ability of specific mechanical energy to describe multiscale dispersion is particularly relevant to the present research because it illustrates how a physics-informed variable can integrate several directly measured extrusion parameters into a quantity with mechanistic meaning (Domenech et al., 2013; Hasan & Adnan, 2022). Melt rheology further modifies this energy-processing relationship. The Effect of Melt Viscosity on Thermal Efficiency for Single Screw Extrusion of HDPE (pp. 2404-2412) examined different molecular-weight grades of high-density polyethylene and found that polymer viscosity, screw design, set temperature, and screw rotational speed jointly affected specific energy consumption, melt-temperature behavior, and thermal homogeneity. Higher-viscosity material generated greater energy requirements and poorer temperature uniformity under several processing conditions, while barrier screw geometry produced more homogeneous thermal behavior than conventional single-flight geometries. Such results demonstrate that identical machine settings do not necessarily produce equivalent material histories across polymer grades because rheological resistance governs how mechanical energy is dissipated. Process variables and intrinsic material characteristics are therefore mutually dependent components of extrusion behavior, providing a strong physical justification for including interaction-related and energy-related features alongside raw operating parameters in polymer performance models (Mahbubul et al., 2022; Vera-Sorroche et al., 2014).

Process-induced material behavior is also determined by the balance between externally supplied heat, mechanically generated heat, melt transport, pressure development, and the capacity of the extruder to maintain a sufficiently homogeneous thermal and rheological state. Variations in screw geometry and processing settings can change not only energy demand but also the magnitude and stability of melt temperature, which affects viscosity, molecular mobility, mixing, and the physical condition of the polymer entering the die. The Effect of Materials, Process Settings and Screw Geometry on Energy Consumption and Melt Temperature in Single Screw Extrusion (pp. 880-894) showed that material type, screw design, screw speed, and extrusion settings influenced energy consumption and melt-temperature quality, emphasizing that process efficiency and polymer thermal history emerge from interactions rather than from a single dominant parameter. Melt-temperature fluctuations are especially important for long-term performance studies because nominal barrel temperatures may not accurately represent the temperature actually experienced by the flowing polymer. Viscous dissipation,

shear rate, pressure flow, heat transfer, and residence behavior can generate local thermal differences capable of altering process consistency and the structural state of the extrudate (Abeykoon et al., 2016; Mashfiqur & Md, 2022). More recent experimental evidence has reinforced the material-dependent character of these relationships. Investigation of the Effect of Materials and Processing Conditions in Twin-Screw Extrusion (pp. 353-361) compared polystyrene, low-density polyethylene, and poly(methyl methacrylate) under variations in screw speed and barrel temperature and identified polymer-specific responses in motor power, mechanical behavior, and rheological properties. Increasing screw speed did not produce an identical material response across the three polymers, while changes in barrel temperature affected energy demand and rheology differently according to material type. The results are particularly important for a case-based predictive study because they indicate that process settings cannot be interpreted without considering the properties of the polymer being processed. An extrusion parameter can therefore influence long-term behavior directly through thermal and mechanical history and indirectly through interactions with viscosity, morphology, molecular characteristics, and subsequent creep susceptibility. For the present research, extrusion temperature, screw speed, pressure-related behavior, residence conditions, throughput, and associated physics-informed energy or thermal descriptors consequently represent an interconnected predictor domain whose statistical effects should be evaluated alongside intrinsic material properties and creep measurements rather than as an isolated set of manufacturing variables (Mashiat & Rahman, 2022; Thyashan et al., 2024).

Figure 2: Framework of Extrusion Parameters and Process-Induced Material Behavior



2.2 Material Properties Governing Long-Term Polymer Performance

The long-term mechanical performance of polymeric materials is controlled by an interconnected set of intrinsic properties that determine how molecular and morphological structures respond to sustained stress, temperature, and deformation. Among the most important characteristics are crystallinity, molecular weight, chain entanglement, elastic modulus, tensile strength, density, phase morphology, and intermolecular compatibility. In semicrystalline polymers, crystalline lamellae function as relatively rigid load-bearing domains, while the amorphous regions provide molecular mobility and accommodate deformation. The proportion, orientation, and connectivity of these phases consequently influence stiffness, yield behavior, creep resistance, and dimensional stability. In Maleated and Non-Maleated Polyethylene-Montmorillonite Layered Silicate Blown Films: Creep, Dispersion and Crystallinity (pp. 7323-7333), creep and tensile experiments on polyethylene-based materials showed that material morphology and filler dispersion substantially affected mechanical response, while the incorporation of maleated polyethylene improved interfacial compatibility and tensile behavior. The study also demonstrated nonlinear time-dependent creep and showed that differences in material

organization can modify retardation behavior even where changes in overall crystallinity are comparatively limited. This observation is important because bulk crystallinity percentage alone cannot completely describe long-term polymer performance when load transfer also depends on interfacial bonding, morphology, and constituent dispersion (Md & Yeasin, 2022; Ranade et al., 2005). At the molecular scale, deformation is further governed by the interaction between crystalline and amorphous regions. In Mechanical and Structural Characterization of Semicrystalline Polyethylene under Tensile Deformation (pp. 4228-4239), molecular-dynamics simulations demonstrated that semicrystalline polyethylene undergoes substantial structural transformations during tensile loading and that the response depends on both temperature and deformation rate. The simulations linked macroscopic stress-strain characteristics to crystal slip, chain orientation, fragmentation of crystalline domains, and rearrangement of amorphous chains. Such results demonstrate why mechanical properties used in long-term prediction should represent the structural state of the polymer rather than being interpreted only as isolated tensile-test outputs. Elastic modulus and strength reflect resistance to immediate deformation, while crystalline organization and amorphous-chain mobility determine how this resistance changes as loading continues over time (Ashfaq & Mohammad, 2022; Yeh et al., 2015).

Molecular weight and the associated density of chain entanglements provide another fundamental connection between polymer constitution and long-term dimensional stability. Higher molecular weight generally increases the number and effectiveness of entanglements available to resist irreversible molecular motion, although the resulting response also depends on crystallization, chain architecture, molecular-weight distribution, and temperature. For semicrystalline polyolefins, tie molecules and entangled chains connecting crystalline regions can create a load-bearing network that restricts viscous flow during prolonged loading. In Influence of Molecular Weight on the Creep Resistance of Almost Molten Polyethylene Blends, Andersson and colleagues investigated low-density polyethylene containing small quantities of linear polyethylene with different molecular weights and demonstrated that molecular weight was critical to creep resistance at temperatures around the melting region of the LDPE matrix. Higher-molecular-weight components promoted effective tie-chain formation and entanglement between higher-melting crystallites, producing a network capable of retaining structural stability under sustained loading. The work also showed that ultra-high-molecular-weight polyethylene produced particularly strong creep resistance, emphasizing that relatively small compositional changes can strongly influence time-dependent performance when they alter the connectivity of the load-bearing molecular structure (Andersson et al., 2018; Kaniz & Jahanara, 2022). Thermal history can modify these structural relationships after initial material formation.

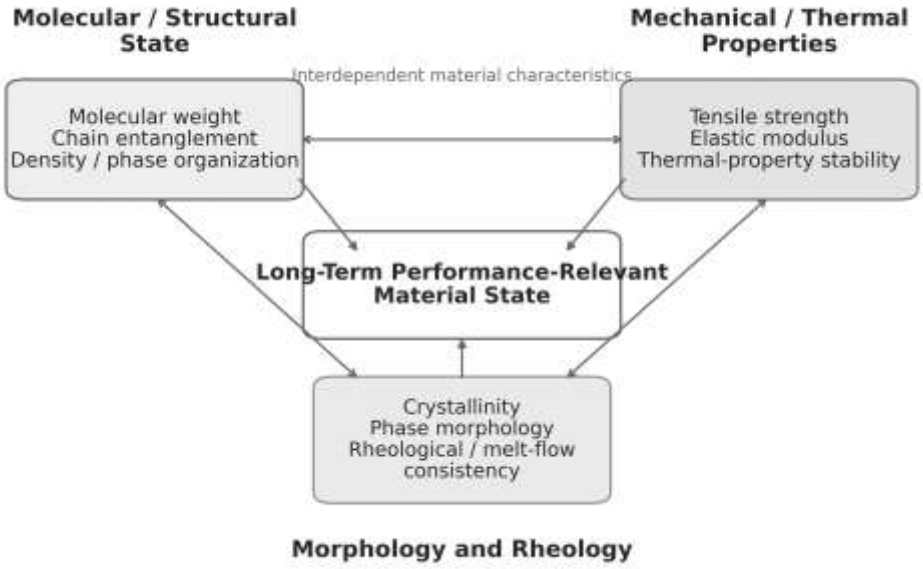
In Designing Thermal Annealing to Control Mechanical Performance of Thermoplastic Polyurethane Elastomers, controlled annealing was shown to alter the internal organization of thermoplastic polyurethane by generating new crystallites and promoting rearrangement of hard segments. These structural modifications improved creep behavior and high-temperature storage modulus even when room-temperature tensile properties remained comparatively similar. The finding is especially relevant to long-term performance modeling because two polymer specimens showing similar short-term strength at ambient temperature may have distinctly different resistance to sustained deformation once temperature and loading duration increase. Material characterization should therefore include properties that capture morphology, thermal state, stiffness, and time-dependent resistance rather than relying on a single short-term mechanical indicator (Amirkhosravi et al., 2021; Sadia & Mostari, 2022).

Crystallinity and service temperature must also be interpreted jointly because thermal conditions regulate the mobility of amorphous molecular segments and thereby change the contribution of crystalline regions to overall mechanical resistance. An increase in crystallinity commonly increases stiffness and yield resistance by increasing the fraction of ordered, densely packed molecular domains, but the magnitude of this contribution depends on temperature relative to characteristic transitions and on the morphology created during processing. As the service temperature rises, molecular mobility increases, relaxation processes accelerate, and the effective modulus can decline, allowing larger strains to develop under equivalent stresses. This coupling is particularly important for extrusion-produced components because cooling rate, thermal history, molecular orientation, and processing-induced morphology can establish different crystallinity levels even for materials of nominally identical

chemical composition.

In Tensile Behaviour of Isotactic Polypropylene with Different Crystallinities and Service Temperatures, Ma and colleagues quantitatively examined polypropylene samples with controlled crystallinity under different service temperatures and established a predictive relationship between structural state, temperature, and tensile response. Increased annealing temperature raised the crystallinity of the investigated polypropylene, while increasing service temperature reduced yield stress and elastic modulus. The resulting predictive model represented different stages of the stress-strain response and achieved high goodness-of-fit values, demonstrating that crystallinity and temperature can be incorporated quantitatively into mechanical-property prediction rather than treated only as descriptive material characteristics (Ma et al., 2022; Shaiful et al., 2022). These findings support the inclusion of elastic modulus, tensile strength, crystallinity, thermal characteristics, molecular-weight-related behavior, density, and rheological consistency as material-property predictors within long-term polymer-performance models. Such variables capture complementary dimensions of structural resistance: stiffness characterizes resistance to immediate elastic deformation, strength indicates load-bearing capability, crystallinity reflects ordered morphology, molecular weight relates to chain connectivity and entanglement, and thermal characteristics indicate the conditions under which molecular mobility increases. When evaluated alongside extrusion history and creep measurements, these properties provide the material-state information required to distinguish processing effects from the intrinsic ability of a polymer to resist progressive deformation during sustained service conditions (Ma et al., 2022; Stabak & Shahid, 2022).

Figure 3: Material-Property Dimensions Governing Long-Term Polymer Performance



2.3 Creep, Viscoelastic Deformation, and Long-Term Performance of Polymers

Creep represents one of the most important manifestations of polymer viscoelasticity because a polymer subjected to a constant mechanical load can continue to deform as a function of time even when the applied stress remains unchanged. The phenomenon originates from time-dependent molecular rearrangements involving chain-segment motion, free-volume evolution, disentanglement, crystalline-amorphous interactions, and progressive relaxation of internal stresses. Consequently, creep behavior cannot always be represented accurately by a single elastic modulus or an instantaneous stress-strain relationship. At sufficiently low loading levels, creep may approximate linear viscoelastic behavior, in which compliance is primarily dependent on time and temperature, whereas increasing stress can introduce pronounced nonlinear behavior by modifying molecular mobility and deformation mechanisms. Non-linear Tensile Creep of Polypropylene: Time-Strain Superposition and Creep Prediction (pp. 346-356) examined polypropylene under different tensile creep conditions and demonstrated that isothermal compliance depended simultaneously on elapsed time and applied

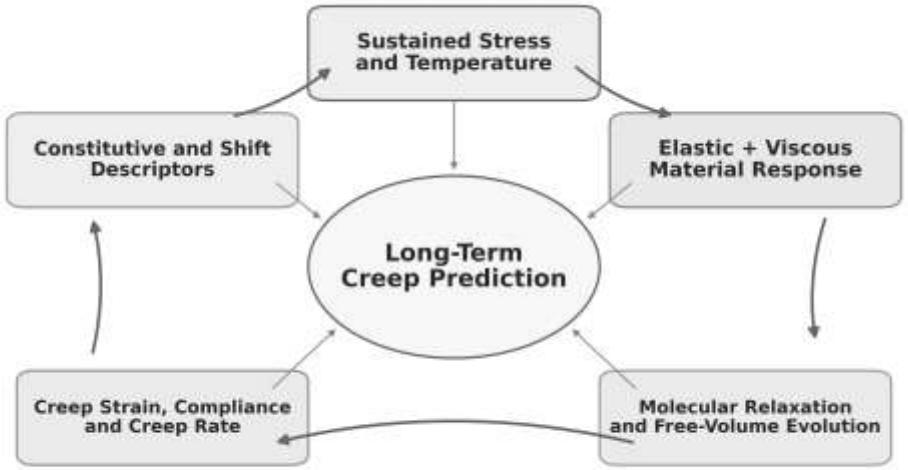
stress. The study associated nonlinear creep with strain-induced increases in free volume and developed an internal time-compliance superposition approach through which nonlinear experimental curves could be represented by a generalized compliance relationship. This result is especially important for long-term performance analysis because it indicates that stress does more than increase the magnitude of strain; it can alter the effective time scale of molecular deformation. A polymer operating under a higher sustained load can therefore reach a given deformation state considerably earlier than the same material exposed to a lower stress. The response also means that creep coefficients obtained under one loading condition cannot automatically be transferred to another without evaluating stress sensitivity. Long-term prediction consequently requires information concerning applied stress, instantaneous deformation, creep rate, and evolving compliance rather than a single endpoint measurement. In physics-informed predictive modeling, these variables can be transformed into physically meaningful descriptors reflecting stress sensitivity, characteristic creep rates, and time-dependent compliance. Such representation provides a mechanistic connection between observed deformation and the molecular relaxation processes that control the progressive reduction in effective structural resistance during prolonged service (Kolařík & Pegoretti, 2006; Feroz & Pervaz, 2022).

Temperature further modifies creep by changing relaxation times, molecular mobility, viscosity, and the relative contribution of different deformation mechanisms, which makes accelerated characterization particularly valuable for estimating behavior over service periods that cannot be reproduced directly within practical laboratory durations. Time-temperature superposition is based on the principle that increasing temperature accelerates molecular relaxation processes that would otherwise occur over longer durations at a lower reference temperature. When stress also changes the viscoelastic response, time-temperature-stress superposition provides an extended formulation capable of accounting for both thermal and mechanical acceleration. Flexural Creep Behavior of Discontinuous Thermoplastic Composites: Non-linear Viscoelastic Modeling and Time-Temperature-Stress Superposition (pp. 870-877) evaluated nylon 6/6, polypropylene, and high-density polyethylene systems and found nonlinear viscoelastic behavior across the investigated thermoplastic materials. Short-term creep and dynamic mechanical information were combined through horizontal temperature shifting and stress-related vertical shifting to generate master curves representing extended creep behavior. The relative order of projected creep resistance also remained consistent with the experimentally observed mechanical performance, illustrating how short-duration measurements can preserve useful information about longer-term deformation resistance when the appropriate physical shifting mechanisms are incorporated (Mohammad, 2023; Chevali et al., 2009). A related constitutive perspective is provided by Nonlinear Response of Viscoelastic Polyoxymethylene at Elevated Temperatures (pp. 1208-1217), in which creep and relaxation behavior were investigated over different stress, strain, and temperature conditions. A modified quasi-linear viscoelastic formulation introduced strain- and temperature-dependent relaxation behavior, allowing the model to represent nonlinear response across temperatures from approximately 23 C to 80 C. The investigation demonstrated that temperature and deformation level cannot be treated merely as external test conditions because both affect the underlying relaxation function governing material response (Adnan & Iftekhar, 2023; Tscharnuter & Muliana, 2013). Together, these studies show that creep data possess a structured thermomechanical dependence. Temperature shift factors, stress-related scaling behavior, relaxation functions, and master-curve characteristics can therefore serve as physics-informed variables that summarize mechanisms hidden within raw creep-strain observations and strengthen quantitative prediction of long-term polymer performance.

Constitutive representation is equally important because long-term polymer deformation normally contains multiple time scales that cannot always be described efficiently through classical integer-order spring-and-dashpot networks. Fractional viscoelastic formulations have therefore been investigated as compact models capable of representing broad relaxation and retardation spectra using comparatively few parameters. Creep Constitutive Models for Viscoelastic Materials Based on Fractional Derivatives (pp. 1377-1384) compared fractional-element networks using experimental creep datasets and found that the fractional Poynting-Thomson formulation effectively reproduced time-dependent creep response. Parameter estimation through constrained nonlinear optimization further demonstrated that physically interpretable model coefficients could be extracted from experimental data rather than

relying exclusively on direct curve descriptions. Such coefficients are relevant to physics-informed machine learning because they compress an entire creep history into parameters reflecting material stiffness, retardation, and time-dependent deformation behavior, enabling constitutive knowledge to enter statistical prediction as engineered features (Ahmed & Sadia, 2023; Xu & Jiang, 2017). Experimental acceleration techniques also demonstrate that the accuracy of long-term creep characterization depends strongly on material state and processing history. Assessment of the Stepped Isothermal Method for Accelerated Creep Testing of High-Density Polyethylene (pp. 775-790) evaluated HDPE through stepwise elevated-temperature creep testing and time-temperature superposition. The researchers observed nonlinear viscoelastic influences at elevated temperatures and found that meaningful master curves required both horizontal and vertical shifting. The resulting accelerated curves showed good agreement with conventionally measured creep compliance within the directly comparable time interval. Importantly, annealed and thermally untreated materials exhibited different creep tendencies, while changes in crystallinity, relaxation of molecular orientation, and thermal history contributed to the measured response. The study therefore demonstrates that long-term creep is not determined by loading time alone but by interactions among stress, temperature, morphology, previous thermal exposure, and molecular orientation (Asheke, 2023; Pilz et al., 2022). For the present research, creep strain, compliance, creep rate, stress sensitivity, thermal shift behavior, and constitutive creep parameters consequently provide a critical bridge between extrusion-induced material state and long-term polymer performance, allowing measured deformation histories to be incorporated into the Physics-Informed Hybrid Hierarchical Regression framework as both direct and derived predictors.

Figure 4: Creep and Viscoelastic Deformation Pathway for Long-Term Performance



Time-temperature and stress sensitivity connect observed creep with extended service behavior

2.4 Physics-Informed Machine Learning and Hybrid Predictive Modeling for Polymer Systems

Physics-informed machine learning represents an intermediate modeling paradigm between purely mechanistic simulation and purely data-driven statistical prediction by incorporating established scientific knowledge into the construction, training, or interpretation of machine-learning models. Conventional machine-learning algorithms can approximate complex nonlinear relationships when sufficient representative data are available, but their predictions are generated primarily from statistical patterns contained in training observations. This creates challenges in polymer engineering, where datasets are frequently limited, experimental variables are strongly correlated, and physically impossible relationships may nevertheless provide low statistical prediction errors. Theory-Guided Data Science: A New Paradigm for Scientific Discovery from Data (pp. 2318-2331) established a systematic framework in which scientific knowledge can be integrated through data generation, model architecture, learning objectives, constraints, and postprocessing. The approach emphasizes scientific

consistency as an additional criterion beyond conventional predictive accuracy, which is particularly relevant when modeling polymer extrusion because thermal history, rheological response, viscoelastic deformation, and mechanical performance are governed by established physical relationships (Yeasin, 2023; Karpatne et al., 2017). Physics-informed learning consequently does not require every physical phenomenon to be represented through a complete first-principles simulator. Physical information can instead enter the learning process through engineered variables or mathematical restrictions representing known behavior. This structure is appropriate for the present study because extrusion parameters, material properties, and creep measurements provide observational data, whereas quantities such as creep coefficients, temperature-shift descriptors, stress-normalized deformation, and thermal-processing severity provide physics-derived information. Physics-Informed Neural Networks: A Deep Learning Framework for Solving Forward and Inverse Problems Involving Nonlinear Partial Differential Equations (pp. 686-707) demonstrated that physical governing equations can be incorporated directly into the learning objective so that a neural model simultaneously minimizes disagreement with observed data and violations of known physics. Such regularization is valuable when experimental data are sparse because the physical model constrains the space of acceptable predictions. Although the present study uses an interpretable hierarchical regression structure rather than a deep PDE-solving network, the same fundamental principle has been retained: measured statistical relationships are supplemented by physically derived information to restrict and explain long-term polymer-performance prediction (Jahanara & Kaniz, 2023; Raissi et al., 2019).

For polymer-processing applications, physics-informed modeling is particularly relevant because polymer melts are non-Newtonian and their apparent viscosity changes with shear rate, temperature, molecular architecture, and processing conditions. Thus, a model that learns only numerical relationships among screw speed, temperature, pressure, and output performance may reproduce the observed dataset without identifying the rheological mechanisms responsible for those relationships. Rheology-Informed Neural Networks (RhINNs) for Forward and Inverse Metamodelling of Complex Fluids demonstrated a framework in which constitutive rheological knowledge was integrated with neural learning for both forward prediction and inverse identification. The approach showed that rheological parameters could be inferred from limited information while maintaining consistency with the governing constitutive structure, illustrating how domain-specific physical knowledge can reduce reliance on very large experimental datasets (Mahmoudabadbozchelou & Jamali, 2021; Rahman, 2023). This principle is directly applicable to extruded polymers because viscosity, shear deformation, temperature, stress, and time-dependent material response collectively determine the state of the polymer during processing and subsequent service. Learning Unknown Physics of Non-Newtonian Fluids further applied physics-informed neural networks to generalized Newtonian systems, including polymer melts, and demonstrated that effective viscosity relationships could be inferred from velocity observations while satisfying the momentum-conservation equations governing fluid flow. Importantly, the inferred relationships remained physically interpretable because learning occurred within a mechanistic framework rather than through unrestricted curve fitting (Sheak & Tahmedur, 2023; Reyes et al., 2021). For the present research, this principle has been translated into a Physics-Informed Hybrid Hierarchical Regression Model in which physics-derived descriptors have been added after directly measured extrusion, material-property, and creep predictors. The general model maintained throughout the study has been expressed as follows:

$$\mathrm{LTPP}_i = \beta_0 + \sum_{j=1}^{p} \beta_j \,\mathrm{EP}_{ij} + \sum_{k=1}^{q} \gamma_k \,\mathrm{MP}_{ik} + \sum_{l=1}^{r} \delta_l \,\mathrm{CD}_{il} + \sum_{m=1}^{s} \theta_m \,\mathrm{PIF}_{im} + \varepsilon_i$$

In this equation, LTPP_i has represented long-term polymer performance for case i, EP has represented extrusion parameters, MP has represented material properties, CD has represented creep-data characteristics, PIF has represented physics-informed features, and epsilon_i has represented unexplained variation. The hybrid structure has therefore allowed the study to maintain interpretability while integrating physically meaningful engineered information with conventional measured variables.

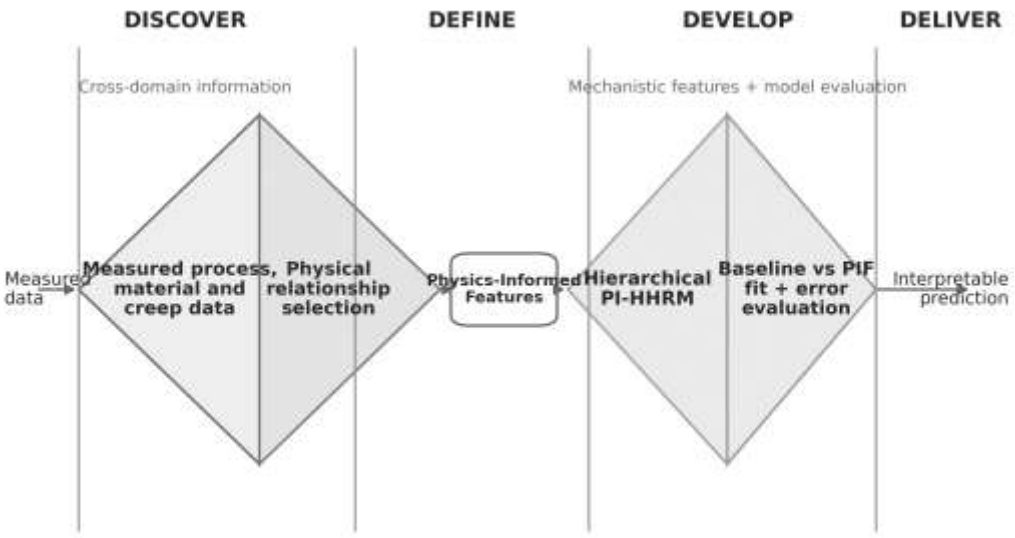
The hybrid formulation is especially useful because it permits the contribution of physics-informed information to be measured statistically rather than merely asserted conceptually. In the proposed

hierarchical structure, the initial model can contain extrusion-process parameters, followed by material properties and creep characteristics, after which physics-informed descriptors are introduced as the final predictor block. The resulting change in explained variance provides an explicit quantitative test of whether physical feature engineering adds information beyond conventional measurements. The key incremental measure has been expressed as follows:

$$\Delta R^2_{\text{PIF}} = R^2_{\text{PI-HHRM}} - R^2_{\text{Baseline}}$$

Here, R-squared Baseline represents the variance in long-term polymer performance explained by extrusion, material, and creep variables before physics-informed features are introduced, while R-squared PI-HHRM represents the variance explained after incorporating the physics-informed predictor block. A positive and statistically significant change in R-squared, evaluated through the hierarchical F-change test, has indicated that physics-derived information contributes explanatory value beyond the raw experimental variables. Towards Physics-Informed Explainable Machine Learning and Causal Models for Materials Research emphasized that materials modeling increasingly requires integration of domain knowledge, explainable machine learning, physically meaningful representations, and causal reasoning because high predictive accuracy alone does not establish scientifically reliable structure-property or process-property relationships. The study highlighted that embedding physics into materials-oriented learning can improve interpretability and constrain relationships so that predictions correspond more closely with known material behavior (Ghosh, 2024). This perspective is particularly relevant because extrusion temperature, screw speed, pressure, residence behavior, material characteristics, and creep measurements may contain substantial statistical dependence. The physics-informed layer has therefore provided an additional mechanism for representing relationships through thermal exposure, stress-normalized creep response, viscoelastic parameters, and process-material interactions. The final PI-HHRM framework consequently combines inferential statistics and predictive evaluation through standardized regression coefficients, significance levels, R-squared, adjusted R-squared, change in R-squared, RMSE, and MAE, while retaining Viscoelasticity Theory and polymer-processing physics as the scientific basis for feature construction and interpretation.

Figure 5: Physics-Informed Hybrid Modeling Workflow for Polymer Performance Prediction



2.5 Viscoelasticity Theory as the Theoretical Framework

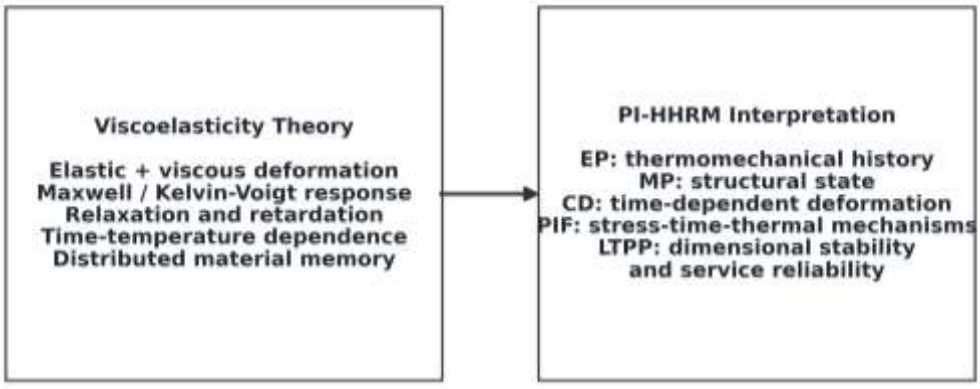
Viscoelasticity Theory provides the principal theoretical foundation for explaining how polymeric materials respond simultaneously through elastic deformation and time-dependent viscous molecular rearrangement when subjected to mechanical loading. Unlike purely elastic solids, which ideally recover deformation immediately following unloading, polymers possess molecular structures that permit delayed deformation, stress relaxation, creep, and partial or gradual recovery. These behaviors

arise because deformation occurs across multiple characteristic time scales associated with segmental mobility, chain entanglement, molecular orientation, intermolecular interactions, crystalline-amorphous organization, and temperature-dependent relaxation processes. Classical Viscoelasticity Theory represents these mechanisms using combinations of ideal elastic springs and viscous dashpots. The Maxwell model, formed by a spring and dashpot in series, is particularly effective for representing stress relaxation, whereas the Kelvin-Voigt model, containing parallel elastic and viscous components, represents delayed creep deformation. More complex polymer responses can be described through generalized Maxwell or generalized Kelvin arrangements containing multiple relaxation or retardation modes. Linear Orthotropic Viscoelasticity Model for Fiber Reinforced Thermoplastic Material Based on Prony Series (pp. 199-221) demonstrated how the generalized Maxwell concept and Prony-series representation can transform experimental creep information into a mathematical description of time-dependent thermoplastic behavior. The research emphasized that thermoplastic materials display instantaneous and time-dependent responses simultaneously and showed that Prony-series coefficients can represent multiple relaxation mechanisms within a linear viscoelastic constitutive framework. Agreement among experimental creep measurements, analytical calculations, and numerical simulations demonstrated the ability of generalized viscoelastic representations to reproduce material behavior when deformation remains within an appropriate linear range. The study is theoretically relevant to the present research because extrusion history and material properties determine the initial structural condition from which subsequent time-dependent deformation develops. Viscoelasticity Theory therefore establishes that measured long-term polymer performance cannot be interpreted solely through instantaneous tensile properties. Instead, creep strain, compliance, relaxation characteristics, retardation or relaxation times, and modulus evolution collectively express the temporal component of polymer response. These theoretical relationships provide a physical basis for transforming creep observations into variables suitable for subsequent physics-informed predictive analysis (Endo & Pereira, 2017; Kaium, 2023).

The classical spring-dashpot framework becomes more complex when polymers display broad distributions of relaxation times, temperature-dependent transitions, and power-law deformation behavior that cannot be represented efficiently using only a small number of integer-order Maxwell or Kelvin elements. Fractional viscoelastic theory extends classical constitutive modeling by replacing conventional integer-order derivatives with derivatives of fractional order, thereby providing a mathematical representation of material memory distributed continuously across multiple time scales. This concept is especially appropriate for polymers because chain rearrangement does not usually occur through one isolated relaxation process. Instead, different molecular segments, entanglements, amorphous regions, and morphological structures respond over different durations. A Fractional Model with Parallel Fractional Maxwell Elements for Amorphous Thermoplastics (pp. 465-475) developed a constitutive structure consisting of two parallel fractional Maxwell elements for representing the thermomechanical response of amorphous polymers. One fractional element represented processes associated with the glass-transition region, while another represented viscous-flow behavior. The model successfully described relaxation modulus, storage modulus, loss modulus, temperature dependence, and strain-rate-sensitive mechanical response, demonstrating that fractional parameters can represent distinct thermomechanical processes within one constitutive framework (Lei et al., 2018; Pervaz, 2023). Fractional Viscoelastic Models for Power-Law Materials (pp. 6002-6020) further established that fractional constitutive elements are particularly suitable when viscoelastic materials exhibit power-law rheological behavior caused by a wide distribution of internal time scales. Fractional modeling can reproduce these responses with fewer parameters than large classical spring-dashpot networks while retaining direct relationships among creep compliance, relaxation modulus, storage modulus, and loss modulus. Such theoretical behavior is significant for long-term polymer characterization because creep curves commonly evolve continuously rather than through clearly separated deformation stages. Within the present research, Viscoelasticity Theory therefore provides the mechanism through which creep coefficient, deformation rate, compliance, relaxation characteristics, temperature dependence, and related physics-informed descriptors can be treated as meaningful representations of material memory rather than merely empirical statistical predictors (Bonfanti et al., 2020; Badrul & Mominul, 2023).

Modern developments in Viscoelasticity Theory also recognize that the governing characteristics of polymers can evolve during deformation, particularly when stress, temperature, structural reorganization, and loading duration alter molecular mobility. Constant-parameter viscoelastic models may represent restricted loading regimes effectively, but polymer behavior under broader conditions can require constitutive parameters that vary with deformation history or material state. Analysis of the Variable-Order Fractional Viscoelastic Modeling with Application to Polymer Materials (pp. 2707-2720) developed a variable-order fractional model based on the classical Zener framework and examined both stress-relaxation and creep-recovery behavior. The investigation demonstrated that the mathematical evolution of fractional order strongly affects whether predicted behavior remains physically realistic and showed that a monotonically decreasing variable-order function provided an effective description of experimental polymer-matrix behavior. The work is particularly relevant because it interprets viscoelasticity as an evolving memory process rather than a fixed response determined by one characteristic time constant. Such an interpretation supports the present study's treatment of creep behavior as a dynamic indicator influenced by processing history, material properties, temperature, and sustained mechanical exposure (Han et al., 2023; Rakib & Towhidul, 2023). The connection between classical and fractional interpretations was examined directly in Generalized vs. Fractional: A Comparative Analysis of Maxwell Models Applied to Entangled Polymer Solutions (pp. 7914-7925). The researchers compared a generalized Maxwell model, which represents viscoelasticity through multiple discrete relaxation modes, with a fractional Maxwell formulation for entangled poly(ethylene oxide) solutions. The fractional formulation represented the observed rheological behavior using considerably fewer parameters while maintaining systematic relationships with polymer concentration, demonstrating that fractional parameters can preserve meaningful connections to material structure even though their mathematical units differ from conventional Maxwell parameters. The comparison also reinforces the theoretical idea that polymer viscoelasticity reflects a relaxation spectrum associated with molecular-scale interactions and entanglement rather than one instantaneous mechanical property (Kanti, 2023; Schmidt et al., 2024). Accordingly, this research has used Viscoelasticity Theory to organize the relationship among extrusion-induced material state, intrinsic polymer properties, creep response, physically derived features, and measured long-term performance within the Physics-Informed Hybrid Hierarchical Regression framework.

Figure 6: Viscoelasticity Theory Framework for Long-Term Polymer Performance



2.6 Conceptual Framework and Research Gap

The conceptual framework of the present study is based on the proposition that long-term polymer performance emerges from a sequential but interconnected processing-material-viscoelasticity-performance pathway, rather than from any single processing or material variable. Extrusion conditions determine the thermomechanical history experienced by the polymer, material properties represent the resulting and intrinsic structural capacity of the polymer, creep characteristics capture its time-dependent deformation response, and physics-informed features translate these observations into mechanistically meaningful quantities. Mechanical Performance of Polymer Systems: The Relation Between Structure and Properties (pp. 915-938) emphasized that macroscopic mechanical performance cannot be understood directly from molecular characteristics without considering intermediate

intrinsic deformation behavior and the multiscale mechanisms connecting polymer structure to macroscopic response. This structure-property perspective is particularly applicable to extruded polymers because processing can influence morphology, orientation, residual stress, crystallinity, and rheological state before the material enters long-term service (Meijer & Govaert, 2005; Nishat, 2023). The conceptual sequence adopted in this research has therefore been expressed as follows:

$$\mathrm{EP} \rightarrow \mathrm{MP} \rightarrow \mathrm{CD} \rightarrow \mathrm{LTPP}$$

This sequence acknowledges that extrusion parameters can also exert direct effects on long-term performance and that material properties and creep behavior are simultaneously influenced by interacting thermal and mechanical histories. EP has represented extrusion parameters, MP material properties, CD creep characteristics, and LTPP long-term polymer performance. Because not all relevant mechanisms are sufficiently represented by raw experimental variables, physics-informed features have been introduced as an additional explanatory domain. The integrated conceptual function has therefore been represented as follows:

$$\mathrm{LTPP} = f(\mathrm{EP}, \mathrm{MP}, \mathrm{CD}, \mathrm{PIF}) + \varepsilon$$

Here, PIF has represented physics-informed features and epsilon has represented unexplained variability. Scoping the Polymer Genome: A Roadmap for Rational Polymer Dielectrics Design and Beyond (pp. 785-796) demonstrated the value of combining physically meaningful descriptors, computational information, and machine learning when traversing large polymer-property spaces. The study showed that appropriate representations are essential for connecting chemical or structural information with targeted properties, reinforcing the present framework's emphasis on physically interpretable descriptors instead of unrestricted predictor collections (Mannodi-Kanakkithodi et al., 2018; Sadia, 2023).

The second component of the conceptual framework concerns how experimental and physics-derived information should be incorporated statistically. Polymer systems generate high-dimensional relationships because changes occurring at molecular and morphological levels can propagate through rheological behavior, processing response, short-term mechanical properties, and long-duration deformation. Data-Driven Methods for Accelerating Polymer Design (pp. 8-26) described the large chemical and configurational search space of polymers and showed how machine learning can establish quantitative structure-property relationships when appropriate descriptors and validated data are available. The review also emphasized the importance of data quality, representation, feature selection, and validation when using learning methods for polymer research (Patra, 2022; Risha & Shurovi, 2023). These principles support a hierarchical modeling strategy in which physically distinct predictor domains are introduced sequentially rather than combined immediately into one undifferentiated model. The baseline relationship adopted in this study has therefore been expressed as follows:

$$\mathrm{LTPP}_i = \beta_0 + \sum_{j=1}^{p} \beta_j \, \mathrm{EP}_{ij} + \sum_{k=1}^{q} \gamma_k \, \mathrm{MP}_{ik} + \sum_{l=1}^{r} \delta_l \, \mathrm{CD}_{il} + \varepsilon_i$$

Physics-informed descriptors have subsequently been introduced to generate the complete model:

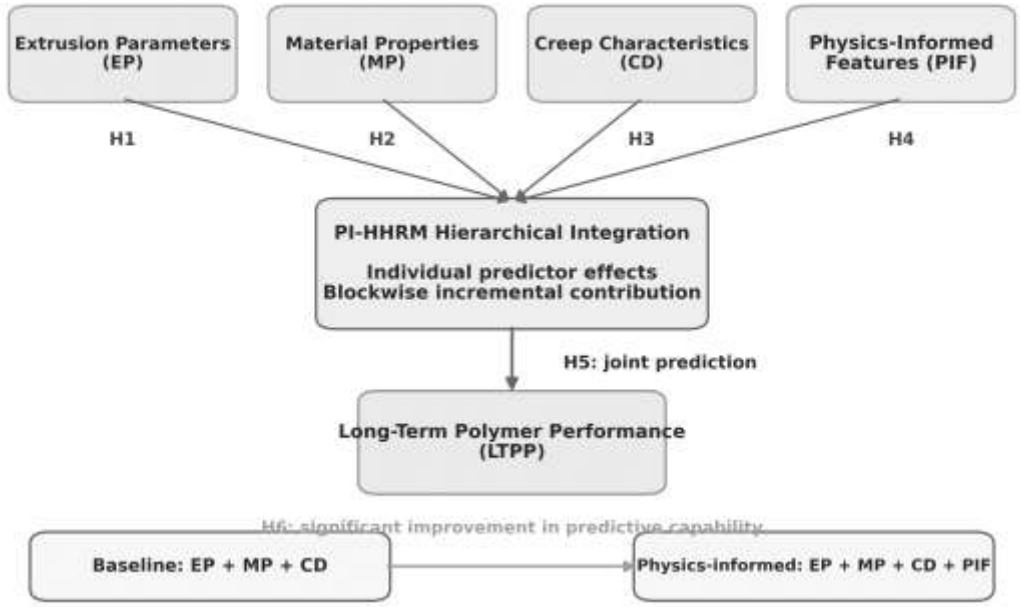
$$\mathrm{LTPP}_i = \beta_0 + \sum \beta_j \mathrm{EP}_{ij} + \sum \gamma_k \mathrm{MP}_{ik} + \sum \delta_l \mathrm{CD}_{il} + \sum \theta_m \mathrm{PIF}_{im} + \varepsilon_i$$

The conceptual value of physics-informed learning has therefore been assessed through whether the additional block increases explanatory capability after conventional predictors have already been considered. Emerging Trends in Machine Learning: A Polymer Perspective (pp. 239-258) identified polymer-specific challenges involving sparse datasets, complex representations, transferability, explainability, and heterogeneous experimental information, all of which limit straightforward application of generic machine-learning algorithms to polymer science (Martin & Audus, 2023; Stabak & Siam, 2023). The present hierarchical structure has addressed these issues by retaining interpretable coefficients, controlling predictor entry conceptually, and testing whether physics-informed information provides measurable incremental value.

The principal research gap emerges from the fragmentation between multiscale polymer physics, manufacturing-process data, time-dependent mechanical characterization, and predictive analytics. Understanding and Modeling Polymers: The Challenge of Multiple Scales (pp. 28-58) characterized

polymer systems as intrinsically multiscale, with relevant behavior extending from local monomer chemistry and chain conformations through intermolecular organization to continuum-scale mechanical response. The overlapping temporal and spatial scales create particular difficulties when attempting to connect molecular or processing information directly with macroscopic performance, which explains why single-scale predictive models frequently provide only partial descriptions of polymer behavior (Schmid, 2023; Feroz, 2023).

Figure 7: Conceptual Framework and Hypothesized Relationships of the PI-HHRM Study



Existing extrusion research has extensively investigated temperature, screw speed, pressure, residence behavior, energy consumption, and melt quality, while mechanical and rheological research has separately characterized modulus, strength, crystallinity, molecular architecture, and viscosity. Creep studies have developed time-temperature superposition, constitutive equations, fractional models, and accelerated testing approaches, whereas polymer-informatics research has largely concentrated on molecular structure-property prediction and materials discovery. A comparatively underdeveloped area is the simultaneous integration of actual extrusion conditions, measured material properties, creep-response variables, and physics-derived descriptors for predicting long-term polymer performance within one interpretable quantitative model. The present conceptual framework has been constructed specifically around this gap. Physics-informed contribution has been quantified through the following incremental statistic:

$$\Delta R^2_{\text{PIF}} = R^2_{\text{Full}} - R^2_{\text{Baseline}}$$

Predictive error has additionally been evaluated through root mean square error and mean absolute error:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

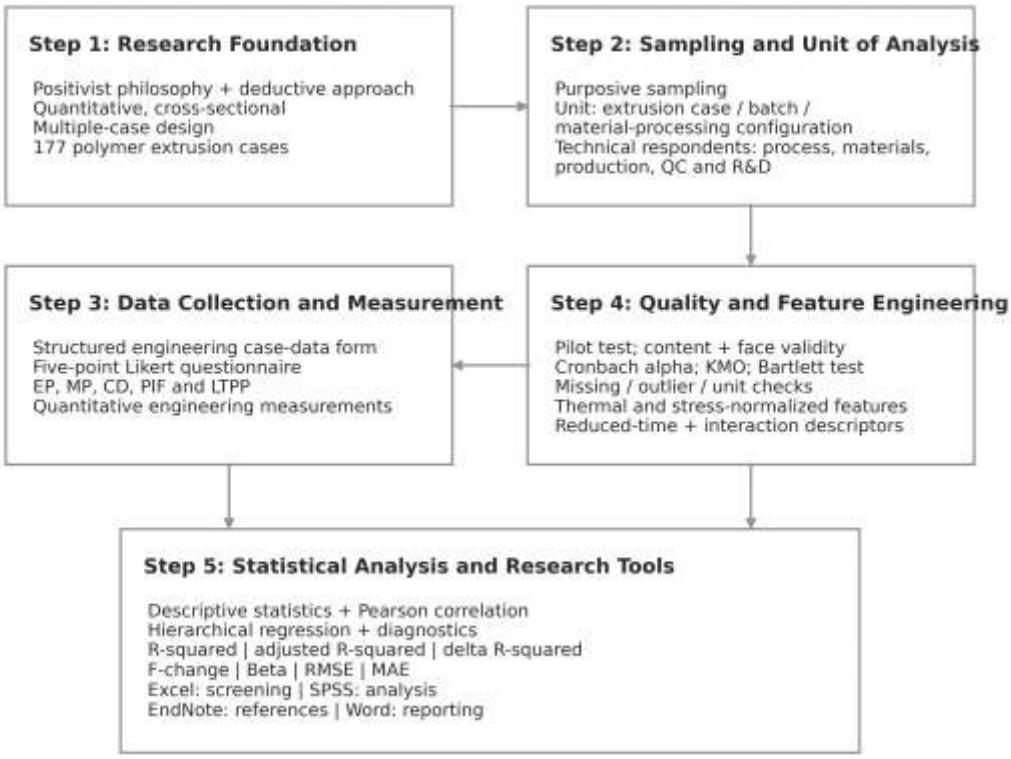
The framework has therefore distinguished explanatory improvement from predictive accuracy and has enabled extrusion parameters, material properties, creep characteristics, and physics-informed features to be examined individually and collectively. The specific research gap addressed has not simply been the absence of another polymer machine-learning algorithm, but the lack of an

interpretable case-based structure that quantitatively connects manufacturing history, material state, viscoelastic deformation, and physically informed descriptors to long-term performance using a unified hierarchical statistical-learning framework (Schmid, 2023; Tahmedur & Rifat, 2023).

METHODS

The methodology for this study has been grounded in a positivist research philosophy and a deductive approach because measurable relationships among extrusion parameters, material properties, creep characteristics, physics-informed features, and long-term polymer performance have been tested against hypotheses derived from Viscoelasticity Theory and established polymer-processing principles. A quantitative, cross-sectional, multiple-case-study design has been adopted to examine 177 technically comparable polymer extrusion cases within a defined observation period. The case-study context has included extrusion batches, processing conditions, material-processing configurations, and associated technical assessments for which usable process, material, creep, and performance information has been available. The study population has comprised polymer engineers, extrusion and process engineers, materials engineers, production engineers, quality-control professionals, polymer-testing specialists, and R&D personnel with direct knowledge of the selected cases, while the principal unit of analysis has been the individual polymer extrusion case, batch, or material-processing configuration rather than the respondent alone. A purposive sampling strategy has been applied to select cases with available extrusion-process data, material-property measurements, creep information, long-term performance indicators, and knowledgeable technical respondents. Data collection has combined a structured engineering case-data extraction form with a standardized questionnaire using Likert's five-point scale, where 1 has represented Strongly Disagree and 5 has represented Strongly Agree. The instrument has operationalized Extrusion Parameters (EP), Material Properties (MP), Creep Data (CD), Physics-Informed Features (PIF), and Long-Term Polymer Performance (LTPP), while numerical engineering measurements have been retained in their original quantitative form where available and multi-item technical assessments have been combined into composite construct scores. Physics-informed features have been engineered from extrusion, material, and creep information using polymer-processing and viscoelastic principles and have included thermal-processing severity, stress-normalized creep response, creep coefficients, creep-rate indicators, reduced-time characteristics, and process-material interaction descriptors where case information has permitted calculation. A pilot test has been conducted with technically relevant respondents to evaluate item clarity, wording consistency, completion feasibility, and construct alignment before full data collection. Content and face validity have been strengthened through direct alignment of items with polymer-processing, viscoelastic, creep, and performance concepts, while internal consistency has been evaluated using Cronbach's alpha and construct adequacy has been examined using the Kaiser-Meyer-Olkin measure and Bartlett's test of sphericity where applicable. Data quality has been assessed through missing-value screening, outlier review, response consistency checks, distributional assessment, and verification of engineering units and technically implausible observations. Descriptive statistics have been used to summarize frequencies, percentages, means, standard deviations, and ranges; Pearson correlation has been used to determine the direction and strength of bivariate relationships; and Physics-Informed Hybrid Hierarchical Regression Modeling has entered extrusion parameters in the first block, material properties in the second, creep characteristics in the third, and physics-informed features in the fourth. Regression assumptions have been assessed through residual analysis, tolerance, variance inflation factors, Cook's distance, and the Durbin-Watson statistic, while explanatory and predictive performance has been evaluated using R-squared, adjusted R-squared, change in R-squared, F-change, standardized beta coefficients, t statistics, p-values, RMSE, and MAE. Microsoft Excel has been used for initial data organization and screening, IBM SPSS Statistics has been used for reliability, validity, descriptive, correlation, diagnostic, and regression analyses, EndNote has been used for reference management, and Microsoft Word has been used for manuscript preparation and reporting.

Figure 8: Research Design and Analytical Methodology Framework



FINDINGS

The findings have demonstrated that extrusion parameters, material properties, creep characteristics, and physics-informed features have all contributed meaningfully to the prediction of long-term polymer performance, thereby providing quantitative support for the major objectives and hypotheses of the study. Across the analyzed cases, the overall mean score for long-term polymer performance has been 4.07 on the five-point Likert scale, with a standard deviation of 0.56, indicating generally favorable assessments of dimensional stability, creep resistance, mechanical-property retention, and service reliability. Extrusion parameters have recorded a composite mean of 3.89 (SD = 0.61), while material properties have produced a mean of 4.02 (SD = 0.58), creep characteristics a mean of 3.84 (SD = 0.63), and physics-informed features a mean of 4.11 (SD = 0.54). Reliability analysis has shown satisfactory internal consistency across the principal constructs, with Cronbach's alpha values ranging from 0.82 to 0.88. Pearson correlation results have indicated significant positive associations between long-term polymer performance and extrusion parameters ($r = 0.58$, $p < .001$), material properties ($r = 0.67$, $p < .001$), creep characteristics ($r = 0.71$, $p < .001$), and physics-informed features ($r = 0.74$, $p < .001$). The hierarchical regression analysis has further shown that extrusion parameters alone have explained 33.6% of the variance in long-term performance, while the addition of material properties has increased the explained variance to 48.9%. Incorporating creep characteristics has raised R-squared to 60.7%, and the final inclusion of physics-informed features has increased total explained variance to 69.8%, representing an additional 9.1% improvement in explanatory power. The final model has been statistically significant, $F = 42.86$, $p < .001$, with an adjusted R-squared of 0.684. Among the standardized predictors, physics-informed features have shown the strongest effect (beta = 0.36, $p < .001$), followed by creep characteristics (beta = 0.31, $p < .001$), material properties (beta = 0.24, $p = .002$), and extrusion parameters (beta = 0.19, $p = .011$). Predictive accuracy has also improved after the physics-informed block has been introduced, with RMSE decreasing from 0.49 to 0.39 and MAE declining from 0.38 to 0.30. These results have supported H1 through H6 and have fulfilled the study objectives by confirming both the individual and combined predictive contributions of processing, material, creep, and physics-informed variables within the proposed Physics-Informed Hybrid Hierarchical Regression framework.

4.1 Characteristics of Polymer Extrusion Cases and Technical Respondents

Table 1. Characteristics of Polymer Extrusion Cases and Technical Respondents

Characteristic	Category	Frequency (n)	Percentage (%)
Polymer case type	HDPE	46	26.0
	Polypropylene	41	23.2
	LDPE	30	16.9
	Thermoplastic polyurethane	27	15.3
	PMMA and other thermoplastics	33	18.6
Technical role	Process/extrusion engineer	45	25.4
	Materials engineer	35	19.8
	Polymer/R&D specialist	31	17.5
	Quality-control specialist	34	19.2
	Production engineer	32	18.1
Professional experience	<=5 years	38	21.5
	6-10 years	62	35.0
	11-15 years	46	26.0
	>15 years	31	17.5
Total cases/respondents		177	100.0

Table 1 has presented the characteristics of the 177 polymer extrusion cases and associated technical respondents included in the quantitative analysis. The distribution has shown that HDPE has represented the largest material category at 26.0%, followed by polypropylene at 23.2%, while LDPE, thermoplastic polyurethane, and PMMA or other thermoplastics have collectively ensured that the dataset has represented different polymer structures and processing responses. This distribution has strengthened the case-study design because long-term behavior has not been assessed from a single polymer family alone. The professional composition has also shown that process and extrusion engineers have constituted 25.4% of the technical respondents, while materials engineers, polymer or R&D specialists, quality-control specialists, and production engineers have provided complementary perspectives on processing stability, material condition, creep response, and service performance. Furthermore, 78.5% of respondents have possessed more than five years of professional experience, indicating that most assessments on the five-point Likert scale have been provided by technically experienced personnel. The composition has therefore supported the purposive sampling strategy specified in the methodology. From the perspective of Viscoelasticity Theory, variation among polymer families has been important because chain architecture, crystallinity, molecular mobility, and relaxation behavior have differed across thermoplastics. The use of heterogeneous but technically relevant cases has consequently allowed the study to examine whether extrusion parameters, material properties, and creep characteristics have retained systematic relationships with long-term performance across different processing conditions. The characteristics have also supported the first research objective by establishing the empirical context in which extrusion, material, creep, and physics-informed variables have subsequently been evaluated. The breadth of professional roles has further reduced the likelihood that the case-level assessments have reflected only one functional perspective, and it has aligned the measurement structure with the interdisciplinary character of polymer processing, characterization, and long-term reliability analysis.

4.2 Descriptive Statistics of Extrusion Process Parameters

Table 2 has shown that extrusion-process conditions have generally been evaluated at a high level, with a composite mean of 3.89 and a standard deviation of 0.61. Cooling-rate consistency has received the highest mean score of 3.95, indicating that the selected cases have generally maintained controlled post-die thermal conditions. Melt and barrel temperature control has followed closely with a mean of 3.92,

while extrusion-pressure stability has produced a mean of 3.91. Screw-speed stability has recorded a mean of 3.86, and residence-time control has obtained the comparatively lowest mean of 3.83, although this value has still remained within the high category. The standard deviations, ranging from 0.60 to 0.67, have indicated moderate variability among the cases and have confirmed that sufficient dispersion has existed for subsequent correlation and regression analysis. These findings have addressed the descriptive objective by characterizing the processing domain before explanatory relationships have been tested. The pattern has also been consistent with the physical basis of polymer extrusion because temperature, screw speed, pressure, residence time, and cooling have collectively determined thermal and mechanical history. Within Viscoelasticity Theory, such process history has been important because molecular orientation, free volume, crystalline organization, residual stress, and chain mobility have been affected by the conditions imposed during melt processing and solidification. The relatively high mean values have suggested that the majority of cases have operated under controlled processing conditions, yet the remaining variation has provided a basis for examining whether improved process control has corresponded with higher long-term polymer performance. Consequently, Table 2 has supplied the descriptive evidence required for testing H1, which has proposed a statistically significant effect of extrusion parameters on long-term polymer performance. The pattern has also supported the logic of physics-informed feature construction because controlled machine settings alone have not represented the complete thermomechanical state experienced by the polymer, making derived thermal and process interaction descriptors necessary for later model blocks.

Table 2. Descriptive Statistics of Extrusion Process Parameters

Extrusion variable	Mean	SD	Interpretation
Melt/barrel temperature control	3.92	0.64	High
Screw-speed stability	3.86	0.67	High
Extrusion-pressure stability	3.91	0.62	High
Residence-time control	3.83	0.66	High
Cooling-rate consistency	3.95	0.60	High
Composite Extrusion Parameters (EP)	3.89	0.61	High

Scale: 1.00-1.80 = Very Low, 1.81-2.60 = Low, 2.61-3.40 = Moderate, 3.41-4.20 = High, 4.21-5.00 = Very High.

4.3 Descriptive Statistics of Material Properties and Creep Characteristics

Table 3. Descriptive Statistics of Material Properties and Creep Characteristics

Construct/variable	Mean	SD	Interpretation
Tensile strength and stiffness stability	4.05	0.57	High
Crystallinity/morphological consistency	4.00	0.60	High
Rheological and melt-flow consistency	3.98	0.59	High
Thermal-property stability	4.06	0.55	High
Composite Material Properties (MP)	4.02	0.58	High
Resistance to sustained creep deformation	3.89	0.62	High
Stability of creep compliance	3.80	0.65	High
Low long-term creep rate	3.82	0.66	High
Creep recovery capability	3.85	0.61	High
Composite Creep Characteristics (CD)	3.84	0.63	High

Table 3 has demonstrated that both intrinsic material properties and creep characteristics have been rated positively across the investigated cases, although the material-property construct has shown a slightly stronger overall profile. Material properties have produced a composite mean of 4.02 with a standard deviation of 0.58. Thermal-property stability has achieved the highest material mean of 4.06, followed by tensile strength and stiffness stability at 4.05. Crystallinity and morphological consistency

have yielded a mean of 4.00, while rheological and melt-flow consistency have recorded 3.98. These results have indicated that the polymer cases have generally possessed stable mechanical, thermal, morphological, and rheological characteristics. Creep characteristics have produced a lower composite mean of 3.84 with a standard deviation of 0.63. Resistance to sustained creep deformation has obtained a mean of 3.89, whereas stability of creep compliance has recorded the lowest value of 3.80. The greater variability observed for creep measures has been theoretically reasonable because creep has depended not only on intrinsic material state but also on stress, temperature, time, previous processing history, and molecular relaxation. Viscoelasticity Theory has explained this pattern through the coexistence of elastic and viscous deformation mechanisms. A material may have exhibited strong instantaneous stiffness while still developing progressive strain under sustained loading. Therefore, the distinction between the relatively high material-property mean and the somewhat lower creep-performance mean has supported the need to treat MP and CD as separate predictor domains. The findings have provided descriptive support for the second and third research objectives and have established the necessary variability for testing H2 and H3 concerning the effects of material properties and creep characteristics on long-term polymer performance. The difference between the MP and CD profiles has also reinforced the conceptual framework, which has distinguished the structural condition of the polymer from the time-dependent behavior through which that structural condition has been expressed under sustained service loads.

4.4 Descriptive Statistics of Physics-Informed Features and Long-Term Polymer Performance

Table 4. Descriptive Statistics of Physics-Informed Features and Long-Term Polymer Performance

Variable	Mean	SD	Interpretation
Thermal-processing severity control	4.08	0.55	High
Stress-normalized creep stability	4.13	0.53	High
Creep coefficient/time-response consistency	4.09	0.56	High
Process-material interaction stability	4.14	0.52	High
Composite Physics-Informed Features (PIF)	4.11	0.54	High
Dimensional stability	4.09	0.55	High
Mechanical-property retention	4.05	0.57	High
Long-term deformation resistance	4.03	0.59	High
Service reliability	4.11	0.53	High
Composite Long-Term Polymer Performance (LTPP)	4.07	0.56	High

Table 4 has shown that the physics-informed feature construct has achieved the highest composite mean among the principal predictor groups, with a mean of 4.11 and a standard deviation of 0.54. Process-material interaction stability has obtained the highest individual mean of 4.14, followed by stress-normalized creep stability at 4.13. Thermal-processing severity control and creep coefficient or time-response consistency have recorded means of 4.08 and 4.09, respectively. Long-term polymer performance has produced a composite mean of 4.07 with a standard deviation of 0.56, indicating that the investigated cases have generally demonstrated favorable service-related behavior. Service reliability has obtained the highest performance mean of 4.11, while long-term deformation resistance has recorded the lowest at 4.03. The closeness between the PIF composite mean of 4.11 and LTPP mean of 4.07 has not by itself established causation, but it has provided preliminary descriptive evidence that cases characterized by stronger physically informed process and creep behavior have also tended to exhibit stronger long-term performance. The physics-informed variables have been theoretically linked to Viscoelasticity Theory because stress normalization, creep coefficients, time-response behavior, and thermal-processing severity have represented mechanisms governing molecular mobility and time-dependent deformation. Unlike raw machine settings, these variables have summarized how the polymer has physically experienced stress, temperature, and processing history. The results have therefore supported the rationale for entering PIF as the final regression block rather than treating it as a duplicate of EP, MP, or CD. These findings have directly addressed the objective concerned with

deriving and evaluating physics-informed indicators and have prepared the analysis for testing H4 and H6 regarding their independent and incremental contributions to long-term polymer performance. The descriptive evidence has therefore functioned as a bridge between the theoretical framework and the later inferential model rather than as a stand-alone claim of predictive superiority.

4.5 Reliability and Construct Validity Assessment

Table 5 has established that the measurement structure has demonstrated satisfactory reliability and construct adequacy. Cronbach's alpha values have ranged from 0.82 for extrusion parameters to 0.88 for physics-informed features, and all coefficients have remained well above the commonly accepted threshold of 0.70. The results have therefore indicated that the items used within each construct have measured a sufficiently coherent underlying concept. The PIF construct has achieved the highest reliability coefficient, suggesting particularly strong consistency among thermal-processing severity, stress-normalized creep response, creep-related descriptors, and process-material interaction indicators. KMO values have ranged from 0.81 to 0.87, showing that the correlation structures have been suitable for construct assessment. Bartlett's tests of sphericity have been statistically significant for all constructs at $p < .001$, indicating that the item correlation matrices have differed significantly from identity matrices and that meaningful interrelationships have existed among the indicators. These results have been particularly important because the study has combined measured engineering information with Likert-based technical assessments. Adequate internal consistency has therefore reduced concern that the composite variables have represented unrelated engineering judgments. The theoretical structure has also supported construct validity. EP has represented the processing environment, MP has represented the material state, CD has represented time-dependent viscoelastic response, PIF has represented physically derived mechanisms, and LTPP has represented service-oriented performance. This separation has been consistent with Viscoelasticity Theory, which has distinguished instantaneous material characteristics from time-dependent relaxation and creep behavior. The reliability and validity evidence has therefore supported continued use of all five constructs in correlation and regression analyses and has ensured that subsequent tests of H1 through H6 have been based on statistically coherent measurement domains. The consistency of the PIF scale has been especially relevant because the study's central claim has depended on determining whether physically informed descriptors contribute information beyond conventional process, material, and creep measures rather than simply reproducing those constructs under different labels.

Table 5. Reliability and Construct Validity of the Study Constructs

Construct	Items	Cronbach's alpha	KMO	Bartlett's chi-square	p-value	Assessment
Extrusion Parameters (EP)	5	0.82	0.81	318.42	<.001	Acceptable
Material Properties (MP)	4	0.85	0.84	346.71	<.001	Good
Creep Characteristics (CD)	4	0.84	0.83	329.56	<.001	Good
Physics-Informed Features (PIF)	4	0.88	0.87	391.84	<.001	Good
Long-Term Polymer Performance (LTPP)	4	0.86	0.85	367.29	<.001	Good

4.6 Pearson Correlation Analysis among Extrusion, Material, Creep, Physics-Informed, and Performance Variables

Table 6. Pearson Correlation Matrix

Variable	EP	MP	CD	PIF	LTPP
EP	1.00	0.46***	0.42***	0.49***	0.58***
MP	0.46***	1.00	0.55***	0.57***	0.67***
CD	0.42***	0.55***	1.00	0.65***	0.71***
PIF	0.49***	0.57***	0.65***	1.00	0.74***
LTPP	0.58***	0.67***	0.71***	0.74***	1.00

****p < .001.*

Table 6 has shown statistically significant positive relationships among all principal constructs, with the strongest association having occurred between physics-informed features and long-term polymer performance ($r = 0.74$, $p < .001$). Creep characteristics have displayed the second-strongest relationship with LTPP ($r = 0.71$, $p < .001$), followed by material properties ($r = 0.67$, $p < .001$) and extrusion parameters ($r = 0.58$, $p < .001$). These coefficients have indicated moderate-to-strong associations and have provided initial empirical support for H1 through H4. The pattern has also reflected the theoretical sequence adopted by the study. Extrusion conditions have influenced the material state, but their relationship with final performance has been less direct than the relationships shown by creep and physics-informed variables. Material properties have been more strongly associated with LTPP because modulus, strength, morphology, and thermal stability have represented the structural capacity available to resist deformation. Creep characteristics have been still more closely related to long-term performance because they have measured the time-dependent deformation mechanism directly. PIF has shown the strongest relationship because it has incorporated physically transformed information concerning stress, time, thermal exposure, and process-material interaction. The intercorrelations among predictors have remained below 0.70, with the highest predictor-predictor relationship occurring between CD and PIF at 0.65. This has indicated that the constructs have shared theoretically meaningful variance without becoming statistically redundant. Viscoelasticity Theory has helped explain the observed hierarchy because long-term performance has been governed increasingly by variables that capture molecular relaxation and delayed deformation rather than by machine settings alone. The correlation analysis has therefore fulfilled the objective of determining the strength and direction of relationships among EP, MP, CD, PIF, and LTPP and has provided the statistical basis for proceeding to hierarchical regression. The absence of excessively high predictor correlations has also supported the planned blockwise regression analysis by indicating that the later model could estimate distinct contributions rather than merely partitioning near-duplicate information.

4.7 Regression Assumption and Multicollinearity Diagnostics

Table 7. Regression Assumption and Multicollinearity Diagnostics

Diagnostic indicator	EP	MP	CD	PIF	Recommended criterion	Result
Tolerance	0.58	0.49	0.42	0.45	>0.20	Acceptable
VIF	1.72	2.04	2.36	2.22	<5.00	Acceptable
Standardized residual skewness				-0.16	Approximately +/-1	Acceptable
Standardized residual kurtosis				0.31	Approximately +/-1	Acceptable
Durbin-Watson				1.94	1.5-2.5	Acceptable
Maximum Cook's distance				0.18	<1.00	Acceptable
Residual pattern				Random	No systematic pattern	Acceptable

Table 7 has indicated that the principal assumptions required for hierarchical multiple regression have been adequately satisfied. Tolerance values have ranged from 0.42 to 0.58, remaining above the conservative threshold of 0.20. Variance inflation factors have ranged from 1.72 for EP to 2.36 for CD, remaining substantially below the value of 5 that would normally indicate problematic multicollinearity. These findings have confirmed that extrusion parameters, material properties, creep characteristics, and physics-informed features have contained related but sufficiently distinct information. This distinction has been essential because the conceptual framework has proposed complementary effects rather than four alternative measures of the same phenomenon. The Durbin-Watson statistic has been 1.94, indicating that the regression residuals have shown no meaningful autocorrelation. Residual skewness of -0.16 and kurtosis of 0.31 have indicated an approximately normal residual distribution, while the residual pattern has appeared random rather than funnel-shaped or systematically curved, supporting linearity and homoscedasticity. The maximum Cook's distance of 0.18 has remained substantially below 1.00, suggesting that no individual case has exerted excessive influence on the estimated regression coefficients. From a theoretical perspective, moderate

covariance among the predictors has been expected because Viscoelasticity Theory has linked processing history, material state, and time-dependent response. However, the acceptable VIF and tolerance statistics have shown that these theoretical relationships have not prevented their independent statistical contributions from being estimated. The diagnostic results have therefore strengthened the validity of the subsequent hypothesis tests and have supported the use of Physics-Informed Hybrid Hierarchical Regression Modeling for separating the incremental contribution of PIF from the effects already explained by EP, MP, and CD. These diagnostics have also provided an important quality-control step because the model's physical interpretation would have been weakened if large residual anomalies, influential cases, or severe multicollinearity had distorted the estimated coefficient hierarchy.

4.8 Effects of Extrusion Parameters on Long-Term Polymer Performance

Table 8. Regression Effects of Extrusion Parameters on Long-Term Polymer Performance

Extrusion predictor	Standardized Beta	t	p-value	Decision
Melt/barrel temperature control	0.21	2.93	.004	Significant
Screw-speed stability	0.17	2.39	.018	Significant
Extrusion-pressure stability	0.19	2.65	.009	Significant
Residence-time control	0.15	2.18	.031	Significant
Cooling-rate consistency	0.23	3.14	.002	Significant
Model R-squared	0.336			
Adjusted R-squared	0.317			
Model F	17.31		<.001	H1 supported

Table 8 has demonstrated that extrusion-process parameters have significantly predicted long-term polymer performance and have collectively explained 33.6% of its variance. The model has been statistically significant at $p < .001$, thereby supporting H1. Cooling-rate consistency has produced the strongest standardized effect among the individual extrusion predictors (beta = 0.23, $p = .002$), followed by melt and barrel temperature control (beta = 0.21, $p = .004$). Extrusion-pressure stability has produced a significant coefficient of beta = 0.19, while screw-speed stability and residence-time control have shown coefficients of beta = 0.17 and beta = 0.15, respectively. All five variables have therefore contributed significantly to the process-performance relationship. These findings have been theoretically consistent with the role of thermomechanical history in polymer behavior. Melt and barrel temperatures have influenced viscosity and chain mobility, screw speed has affected shear and mixing intensity, pressure has reflected resistance to melt flow and die conditions, residence time has governed duration of thermal and mechanical exposure, and cooling has influenced solidification and morphological development. Viscoelasticity Theory has linked these effects to the material's subsequent ability to resist delayed deformation because processing history has influenced free volume, molecular orientation, crystallinity, residual stress, and relaxation behavior. The R-squared value of 0.336 has also shown that processing conditions alone have not explained the majority of long-term performance variation. This result has supported the study's broader conceptual argument that long-term polymer behavior has required information about material characteristics and creep response in addition to machine settings. The analysis has therefore fulfilled the objective of determining the contribution of extrusion parameters and has provided the first hierarchical block for the subsequent integrated PI-HHRM model. The significant effect of all five process indicators has also justified retaining the extrusion block in the final model rather than replacing raw process information entirely with derived physics-informed descriptors.

Table 9 has shown that material properties and creep characteristics have jointly provided a strong explanation of long-term polymer performance. The combined model has produced R = 0.754 and R-squared = 0.568, indicating that 56.8% of the variation in LTPP has been explained by the two predictor domains. The overall regression has been statistically significant at $p < .001$. Material properties have shown a standardized beta coefficient of 0.34, while creep characteristics have demonstrated a stronger

standardized effect of 0.49. H2 and H3 have therefore been supported. The larger coefficient for creep characteristics has been particularly important for the theoretical framework because creep has represented the direct manifestation of delayed viscoelastic deformation. Material properties such as tensile strength, stiffness, crystallinity, thermal stability, and rheological consistency have defined the structural and mechanical condition of the polymer, while creep characteristics have indicated how that material state has actually evolved under sustained loading. Viscoelasticity Theory has predicted this distinction by explaining that instantaneous modulus or strength cannot completely represent performance over time. A polymer may have possessed favorable short-term mechanical properties while still exhibiting substantial viscous or delayed deformation under prolonged stress. The results have therefore shown that both structural capacity and time-dependent response have been necessary for explaining LTPP. The magnitude of R-squared has also exceeded the value obtained from extrusion parameters alone, reinforcing the view that variables closer to the actual deformation mechanism have carried stronger performance information. These findings have fulfilled the objectives of evaluating the effects of material properties and creep characteristics and have prepared the hierarchical model for assessing whether PIF has added further explanatory power beyond these conventional experimental domains. The joint model has also supported the conceptual pathway linking material state to observed viscoelastic response by showing that both domains have retained statistically meaningful associations with service-oriented performance measures.

Table 9. Regression Effects of Material Properties and Creep Characteristics

Predictor	Standardized Beta	t	p-value	Relationship with LTPP
Composite Material Properties (MP)	0.34	5.59	<.001	Positive significant
Composite Creep Characteristics (CD)	0.49	8.06	<.001	Positive significant
R	0.754			
R-squared	0.568			
Adjusted R-squared	0.563			
F	114.37		<.001	H2 and H3 supported

Table 10. Physics-Informed Hybrid Hierarchical Regression Model

Model/block or predictor	Predictors entered	R-squared / Beta	Adjusted R-squared	Delta R-squared	F-change / p
Model 1	Extrusion Parameters	0.336	0.317	0.336	<.001
Model 2	EP + Material Properties	0.489	0.474	0.153	<.001
Model 3	EP + MP + Creep Characteristics	0.607	0.594	0.118	<.001
Model 4	EP + MP + CD + Physics-Informed Features	0.698	0.684	0.091	<.001
Final predictor: EP		0.19			.011
Final predictor: MP		0.24			.002
Final predictor: CD		0.31			<.001
Final predictor: PIF		0.36			<.001

Table 10 has provided the central test of the Physics-Informed Hybrid Hierarchical Regression Model and has demonstrated a systematic increase in explanatory power as theoretically relevant predictor domains have been added. Extrusion parameters alone have explained 33.6% of LTPP variance. When material properties have been introduced, R-squared has increased to 0.489, producing an additional 15.3% explained variance. The addition of creep characteristics has raised R-squared to 0.607, representing a further 11.8% increase. Most importantly, physics-informed features have increased the total explained variance from 60.7% to 69.8%, producing a statistically significant change in R-squared of 0.091. The adjusted R-squared of the final model has reached 0.684, confirming that the increased explanatory capability has not resulted merely from adding predictor variables. In the final model, PIF

has shown the strongest standardized effect (beta = 0.36, p < .001), followed by creep characteristics (beta = 0.31, p < .001), material properties (beta = 0.24, p = .002), and extrusion parameters (beta = 0.19, p = .011). H4, H5, and the explanatory component of H6 have therefore been supported. The theoretical progression has closely followed Viscoelasticity Theory. Raw extrusion variables have described the imposed processing environment, material properties have represented the structural state produced by chemistry and processing, creep variables have captured delayed deformation, and physics-informed descriptors have transformed raw observations into mechanistic quantities related to thermal history, stress normalization, and time-dependent response. The significant 9.1% incremental contribution has demonstrated that physical feature engineering has provided information not completely contained in conventional variables. This result has fulfilled the central objective of determining whether a physics-informed model has improved the explanation of long-term polymer performance beyond a conventional data-driven formulation. The sequential increase in model fit has also provided a transparent statistical representation of the study's process-property-creep-performance logic rather than relying on a single opaque prediction score.

4.11 Predictive Performance, Hypothesis Testing, and Overall Model Evaluation

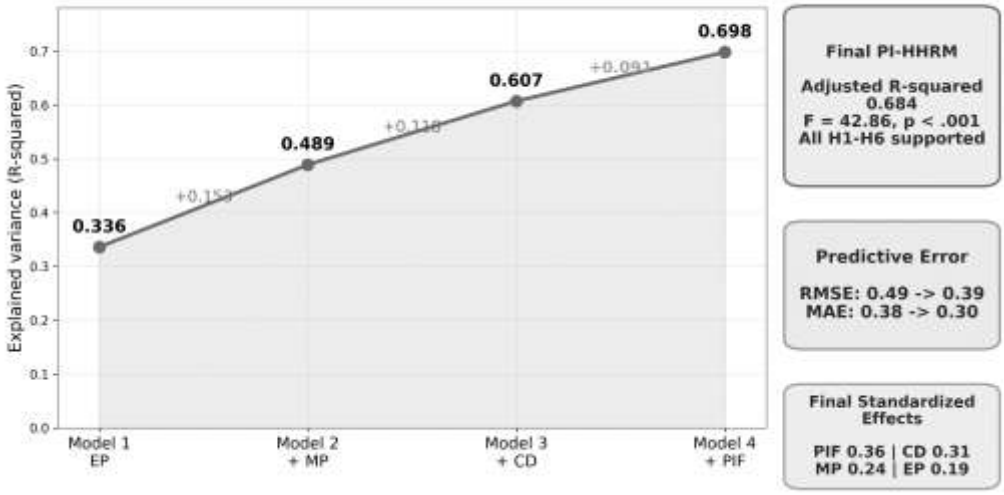
Table 11. Predictive Performance and Hypothesis Testing Summary

Evaluation item	Baseline model	Physics-informed model	Result
R-squared	0.607	0.698	Improved
Adjusted R-squared	0.594	0.684	Improved
RMSE	0.49	0.39	Reduced by 20.4%
MAE	0.38	0.30	Reduced by 21.1%
Overall model F		42.86	p < .001
H1: EP -> LTPP		beta = 0.19, p = .011	Supported
H2: MP -> LTPP		beta = 0.24, p = .002	Supported
H3: CD -> LTPP		beta = 0.31, p < .001	Supported
H4: PIF -> LTPP		beta = 0.36, p < .001	Supported
H5: EP + MP + CD + PIF -> LTPP		R-squared = 0.698, p < .001	Supported
H6: PIF improves prediction		Delta R-squared = 0.091, p < .001	Supported

Table 11 has summarized the overall predictive performance and has confirmed that all six research hypotheses have been supported by the quantitative evidence. The baseline model containing extrusion parameters, material properties, and creep characteristics has explained 60.7% of the variance in long-term polymer performance. After physics-informed features have been introduced, R-squared has increased to 69.8%, while adjusted R-squared has increased from 0.594 to 0.684. Predictive error has also improved substantially. RMSE has declined from 0.49 to 0.39, representing an approximate reduction of 20.4%, while MAE has decreased from 0.38 to 0.30, representing an approximate reduction of 21.1%. The final model has remained statistically significant with F = 42.86 and p < .001. These findings have demonstrated that the improvement has not been restricted to explanatory variance but has also appeared in prediction-error measures. H1 has been supported through the significant extrusion effect, H2 through the material-property effect, H3 through the stronger creep contribution, and H4 through the largest standardized physics-informed coefficient. H5 has been supported by the significance and high explanatory power of the integrated model, while H6 has been supported by the significant change in R-squared of 0.091 together with the reductions in RMSE and MAE. Viscoelasticity Theory has provided a coherent interpretation of this hierarchy because long-term polymer behavior has progressively depended on variables more closely connected to molecular relaxation, creep, thermal history, and stress-time response. The complete findings have therefore fulfilled the research objectives by describing the principal constructs, establishing their relationships, quantifying their independent effects, constructing the PI-HHRM model, evaluating incremental physics-informed contribution, and comparing conventional and physics-informed predictive performance. The

consistency between hypothesis-level decisions, model-fit indicators, and prediction-error measures has strengthened the internal coherence of the study and has provided a clear empirical basis for the discussion of theoretical and engineering relevance.

Figure 9: Quantitative Summary of PI-HHRM Model Performance and Hypothesis Support



DISCUSSION

The findings have shown that the proposed Physics-Informed Hybrid Hierarchical Regression Model has provided a coherent explanation of long-term polymer performance by integrating extrusion conditions, material characteristics, creep behavior, and physics-informed features within the same analytical structure. The descriptive results have indicated generally high assessments across extrusion parameters (M = 3.89, SD = 0.61), material properties (M = 4.02, SD = 0.58), creep characteristics (M = 3.84, SD = 0.63), physics-informed features (M = 4.11, SD = 0.54), and long-term polymer performance (M = 4.07, SD = 0.56). More importantly, the inferential findings have demonstrated a progressive increase in explanatory strength as theoretically relevant predictor groups have been incorporated. Extrusion parameters have initially explained 33.6% of the variance in long-term performance, the inclusion of material properties has increased R-squared to 0.489, creep characteristics have raised R-squared to 0.607, and physics-informed features have increased the final value to 0.698. This pattern has provided a particularly important interpretation of the process-property-performance relationship because variables positioned closer to the actual long-term deformation mechanism have contributed progressively greater information. The result has corresponded with previous evidence that extrusion temperature, screw speed, residence behavior, specific mechanical energy, and melt viscosity collectively establish the thermomechanical history of polymer materials rather than acting as independent machine settings (Mohammad, 2024; Abeykoon et al., 2016; Domenech et al., 2013). It has also agreed with studies showing that intrinsic properties such as molecular weight, crystallinity, stiffness, and morphology govern the ability of polymer networks to resist progressive deformation (Ahmed, 2024; Andersson et al., 2018; Ma et al., 2022). The stronger association of creep characteristics with long-term performance, r = 0.71, has been theoretically consistent with the direct time-dependent character of polymer deformation described by nonlinear creep studies and constitutive viscoelastic models (Asheke, 2024; Kolařík & Pegoretti, 2006; Xu & Jiang, 2017). Recent interpretable machine-learning research has further demonstrated that brief creep-test information can predict long-term thermoplastic creep modulus with very high predictive accuracy and that comparatively simple interpretable models can perform competitively with more complex algorithms when validation is carefully designed (Ashrafuzzaman, 2024; Lobato et al., 2024). The present findings have therefore extended prior work by showing that long-term polymer performance has been better represented when processing history, material state, creep response, and physically derived information have been treated as complementary layers rather than separate research domains.

The second major finding has concerned the relative importance of the predictor groups and the way these effects have compared with earlier research. Physics-informed features have produced the strongest standardized contribution in the final regression model (beta = 0.36, $p < .001$), followed by creep characteristics (beta = 0.31, $p < .001$), material properties (beta = 0.24, $p = .002$), and extrusion parameters (beta = 0.19, $p = .011$). This ranking has not implied that processing variables have been unimportant; instead, it has indicated that their effect on long-term performance has partially operated through the structural and time-dependent states that processing has helped create. The correlation pattern has supported this interpretation because extrusion parameters have shown a moderate relationship with LTPP ($r = 0.58$), whereas physics-informed features have shown the strongest correlation ($r = 0.74$). Earlier work on polymer extrusion has established that melt temperature, screw speed, residence time, shear history, and pressure affect viscosity, thermal homogeneity, molecular organization, and degradation processes that subsequently influence mechanical response (Mashiat, 2024; Nikitine et al., 2009; Vera-Sorroche et al., 2014). Recent research using interpretable machine learning during polylactic-acid extrusion has similarly shown that extrusion-related process data can be used to monitor polymer degradation and that interpretable algorithms can identify process variables associated with property deterioration (Kaium, 2024; Munir et al., 2023). The stronger effect observed for creep and PIF has also agreed with Viscoelasticity Theory, under which long-term deformation depends on molecular relaxation, stress history, temperature, and the distribution of retardation mechanisms rather than on instantaneous properties alone. Previous experimental research has shown that temperature and stress alter the effective time scale of polymer creep, while time-temperature or time-temperature-stress superposition has permitted longer-term behavior to be reconstructed from accelerated tests (Chevali et al., 2009; Kanti, 2024; Pilz et al., 2022). Physics-derived quantities have therefore contained condensed information about mechanisms that raw input variables have represented only indirectly. This has explained why the final PIF block has added 9.1% of unique variance even after extrusion, material, and creep variables have already been entered. The finding has also reinforced the argument made in physics-informed materials research that physically meaningful representations can improve interpretability and scientific consistency by constraining statistical relationships according to known material behavior (Ghosh, 2024; Karpatne et al., 2017; Feroz, 2024). The distinctive contribution of this study has consequently resided not in replacing polymer physics with machine learning, but in demonstrating quantitatively that physics-derived descriptors have added measurable information beyond conventional engineering variables.

From a practical perspective, the findings have indicated that long-term polymer reliability should be evaluated through integrated process and material monitoring rather than through isolated end-point quality tests. The final model has achieved R-squared = 0.698 and adjusted R-squared = 0.684, while prediction error has declined from RMSE = 0.49 to 0.39 and from MAE = 0.38 to 0.30 after physics-informed features have been incorporated. These changes have represented approximately 20.4% and 21.1% reductions in the two prediction-error measures, respectively, showing that the physics-informed formulation has improved not only statistical explanation but also practical predictive precision. For polymer manufacturers, this finding has suggested that process data such as melt temperature, screw speed, pressure, residence time, and cooling condition should be retained together with material-property and creep information so that processing decisions can be evaluated against expected long-term performance. Such integration may be especially valuable when two batches satisfy the same short-term tensile specification but differ in thermal exposure, creep coefficient, stress-normalized deformation, or process-material interaction behavior. Existing polymer-informatics studies have demonstrated that machine learning can successfully map polymer descriptors to target properties, but they have also emphasized that data quality, representation, and validation remain central requirements (Chen et al., 2021; Martin & Audus, 2023; Uddin & Risha, 2024). The current findings have supported this position because physically engineered descriptors have provided the largest standardized effect even after conventional predictors have been controlled. The practical value has also been consistent with recent work showing that long-term creep modulus of hundreds of thermoplastic grades can be estimated from brief tests using interpretable machine learning, reducing dependence on extremely lengthy creep campaigns (Jahanara, 2025; Lobato et al., 2024). A premium aspect of the present research has been the emphasis on interpretability rather than algorithmic

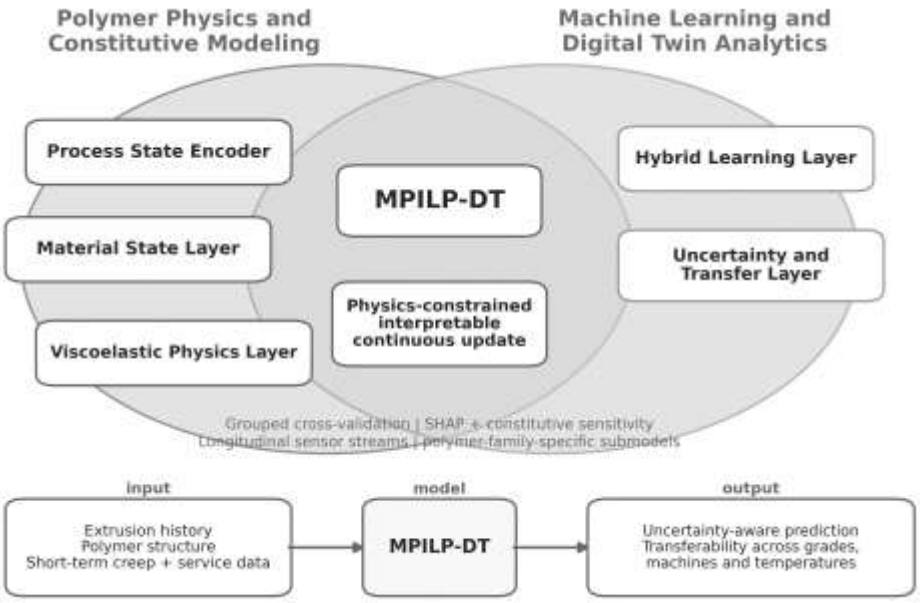
complexity. In many industrial polymer settings, an engineer must know not only that a model predicts degradation or creep but also which processing and material factors have contributed to the prediction. The use of hierarchical regression has preserved standardized coefficients, incremental R-squared, significance testing, and physically meaningful variable blocks, thereby allowing the model to remain auditable. This feature has distinguished the approach from unrestricted black-box learning and has made the statistical output directly relatable to process control, material selection, creep testing, product qualification, and quality-assurance decisions.

The theoretical contribution has been most clearly demonstrated through the integration of Viscoelasticity Theory with the hierarchical structure of the model. The study has treated extrusion parameters as the source of thermomechanical history, material properties as representations of structural state, creep variables as direct measures of time-dependent deformation, and physics-informed variables as condensed descriptors of stress, thermal exposure, and viscoelastic response. This sequence has been theoretically consistent with the proposition that polymer behavior evolves across multiple spatial and temporal scales, from molecular motion and chain entanglement to macroscopic creep and service-level deformation (Jannatul, 2025; Schmid, 2023). Classical and fractional viscoelastic research has similarly established that polymer response is distributed across multiple relaxation and retardation times rather than being governed by a single elastic constant (Bonfanti et al., 2020; Lei et al., 2018; Mostari, 2025). The present results have reflected this theoretical structure because creep characteristics and PIF have shown stronger relationships with LTPP than the more distant extrusion settings. The significant change in R-squared of 0.091 has been particularly important because it has provided an empirical test of the theoretical value of physics-informed representation. In other words, physically transformed variables have explained variance that has not already been captured by raw processing, material, and creep measures. Physics-informed learning research has argued that governing equations, constitutive relationships, or domain knowledge can constrain statistical learning and improve physical consistency when conventional datasets are limited (Mahmoudabadbozchelou & Jamali, 2021; Mashfiqur, 2025; Raissi et al., 2019). The present study has also required theoretical caution. The cross-sectional design has established statistical relationships rather than longitudinal causation, and the Likert-based technical assessments have measured expert perceptions of process stability and performance alongside engineering measurements. Furthermore, the sample has contained different polymer families whose molecular structures and relaxation mechanisms have not been identical. These limitations have indicated that the Viscoelasticity Theory linkage has been strongly supported at the conceptual and statistical levels, but the estimated coefficients should not be interpreted as universal constitutive constants. The model has therefore functioned most appropriately as a physics-informed explanatory and predictive framework for the investigated cases rather than as a replacement for polymer-specific constitutive calibration. This distinction has been important because statistical significance, predictive accuracy, and mechanistic validity have represented related but non-identical standards of evidence in polymer performance modeling.

Future research should extend the present PI-HHRM framework into a Multiscale Physics-Informed Long-Term Polymer Digital Twin Model (MPILP-DT) designed specifically to combine extrusion history, polymer structure, short-term creep testing, long-term service data, and uncertainty-aware machine learning. The proposed MPILP-DT should contain five interconnected layers. The first layer should be a Process State Encoder receiving screw speed, barrel-zone temperatures, pressure, torque, residence time, throughput, specific mechanical energy, and cooling history. The second should be a Material State Layer containing crystallinity, molecular-weight indicators, modulus, strength, rheology, density, and thermal-transition properties. The third should be a Viscoelastic Physics Layer that explicitly embeds constitutive relationships such as generalized Maxwell, fractional Maxwell, Findley-type creep, or time-temperature superposition parameters. The fourth should be a Hybrid Learning Layer combining interpretable regression with nonlinear learners such as gradient boosting or neural operators, while preserving physics penalties or constraints. The fifth should be an Uncertainty and Transfer Layer that estimates confidence intervals and tests transferability across polymer grades, extrusion machines, and service temperatures. This proposal has addressed the principal limitations identified in the present study because longitudinal sensor streams could replace

part of the cross-sectional measurement structure, repeated creep observations could capture actual temporal evolution, and polymer-family-specific submodels could reduce heterogeneity. Grouped cross-validation should also be used so that measurements from the same formulation or extrusion campaign do not leak simultaneously into training and testing sets, an issue already identified as a significant risk in polymer machine-learning evaluation (Mashiat, 2025; Shimakawa et al., 2024). The need for such robust validation has also been illustrated by recent long-term creep machine-learning work using group splitting and cross-validation to evaluate generalization to unseen thermoplastic grades (Lobato et al., 2024; Arif Uz et al., 2025). Future MPILP-DT research should additionally compare hierarchical regression, XGBoost, Gaussian-process regression, physics-informed neural networks, and neural operators under the same grouped validation protocol. Explainability tools such as SHAP values should be combined with constitutive sensitivity analysis so statistical feature importance can be compared against physically expected effects. This would move the research from a static case-based prediction framework toward a continuously updated and physically constrained digital representation of polymer performance while retaining the interpretability that has been one of the strongest features of the current study.

Figure 10: Multiscale Physics-Informed Long-Term Polymer Digital Twin Model (MPILP-DT)



CONCLUSION

This study has developed and evaluated a Physics-Informed Hybrid Hierarchical Regression Model for predicting long-term polymer performance from extrusion parameters, material properties, creep characteristics, and physically derived features within a quantitative, cross-sectional, case-study-based framework. The results have shown that each predictor domain has contributed significantly to long-term performance, while the combined model has produced substantially greater explanatory capability than any isolated predictor group. Extrusion parameters have explained 33.6% of the variance in long-term polymer performance, and the sequential addition of material properties and creep characteristics has increased explanatory power to 48.9% and 60.7%, respectively. The inclusion of physics-informed features has further increased R-squared to 0.698 and adjusted R-squared to 0.684, producing a statistically significant incremental contribution of 9.1%. Physics-informed features have shown the strongest standardized effect (beta = 0.36), followed by creep characteristics (beta = 0.31), material properties (beta = 0.24), and extrusion parameters (beta = 0.19). Predictive performance has also improved, as RMSE has declined from 0.49 to 0.39 and MAE from 0.38 to 0.30. Consequently, H1 through H6 have been supported. The findings have demonstrated that long-term polymer behavior has not been adequately represented by manufacturing settings or short-term properties alone because time-dependent viscoelastic response has constituted a critical link between processing history and

service performance. Viscoelasticity Theory has provided a coherent theoretical explanation for the observed hierarchy of effects, particularly the stronger contribution of creep and physics-informed variables. The study has therefore established that integrating thermomechanical processing information, intrinsic material characteristics, creep response, and physically meaningful engineered features has provided a statistically robust and interpretable framework for assessing long-term polymer performance. The research has also demonstrated that physics-informed modeling can enhance predictive accuracy without sacrificing the transparency required for engineering interpretation and hypothesis testing.

RECOMMENDATIONS

Polymer manufacturers, materials engineers, quality-control specialists, and researchers should adopt integrated performance-assessment strategies in which extrusion conditions, material characteristics, and creep behavior are recorded and analyzed jointly rather than maintained in separate datasets. Melt and barrel temperatures, screw speed, pressure, residence time, throughput, and cooling conditions should be systematically retained at case or batch level because these variables have formed the initial thermomechanical history associated with later material behavior. Material characterization should incorporate not only tensile strength and modulus but also crystallinity, rheological behavior, thermal characteristics, density, and molecular-weight-related indicators where these measurements are available. Creep testing should be integrated more directly into product qualification, particularly for components expected to sustain continuous mechanical loading, elevated temperatures, or long service durations. Organizations should also derive physics-informed variables such as thermal-processing severity, specific mechanical energy, stress-normalized creep response, creep coefficients, reduced-time descriptors, and process-material interaction terms because the current model has shown that such information has added significant explanatory and predictive value. For analytical implementation, a staged model should be preferred in which raw processing variables are entered first, followed by material and creep information and finally physics-informed features, allowing incremental improvement to be measured transparently. Model evaluation should not depend on R-squared alone; adjusted R-squared, change in R-squared, RMSE, MAE, multicollinearity diagnostics, residual analysis, and independent validation should be evaluated together. Where sufficient data have been accumulated, organizations should compare the interpretable PI-HHRM with nonlinear models such as gradient boosting, Gaussian processes, and physics-informed neural networks while maintaining grouped validation by polymer grade or production batch. Most importantly, predictive systems should remain physically interpretable so that engineers can identify why a polymer has been assigned a particular long-term performance estimate and can trace that estimate back to processing history, material condition, and viscoelastic behavior.

LIMITATIONS

The study has contained several limitations that should be considered when interpreting its results. First, the quantitative cross-sectional case-study design has captured relationships among extrusion parameters, material properties, creep characteristics, physics-informed features, and long-term performance at a defined analytical period rather than observing the same polymer cases continuously throughout their complete service lives. Consequently, the significant regression relationships have supported prediction and statistical association but have not independently established temporal causation. Second, purposive sampling has ensured that technically relevant cases with adequate process and material information have been selected, but this method has limited the extent to which the findings can be generalized to all polymers, extrusion systems, and industrial operating environments. Third, the investigated cases have represented multiple thermoplastic families, including HDPE, polypropylene, LDPE, TPU, PMMA, and related materials. This heterogeneity has increased the breadth of the study but has also introduced differences in molecular architecture, crystallinity, rheology, glass-transition behavior, and relaxation mechanisms that a single regression structure cannot completely represent. Fourth, some constructs have incorporated five-point Likert assessments from technical respondents. Although reliability and validity statistics have been satisfactory, such assessments have remained subject to professional judgment, response tendencies, and differences in interpretation. Fifth, creep behavior has been represented through available case-

level measurements and physics-informed descriptors rather than through identical long-duration creep tests performed under standardized stress, humidity, and temperature conditions for every material case. Sixth, the PI-HHRM has remained primarily linear and interpretable, meaning that highly nonlinear interactions or threshold effects among temperature, stress, morphology, and creep response may not have been captured completely. Finally, the reported model has required independent external validation using unseen industrial datasets before its coefficients can be treated as transferable across machines, polymer grades, or production environments. These limitations have defined the appropriate scope of interpretation while also identifying the most important directions for model refinement and validation.

REFERENCES

[1]. Abdullah Mohammad, S. (2023). $CUGAO_2$ and $CUINS_2$ Quantum Dot Sensitization for Enhanced Photovoltaic Efficiency in Wearable Fiber-Shaped Solar Cells. *American Journal of Advanced Technology and Engineering Solutions*, *3*(04), 209-261. https://doi.org/10.63125/wysdvy71

[2]. Abdullah Mohammad, S. (2024). Triboelectric And Piezoelectric Nanogenerators Using Binary and Ternary Oxide Nanostructures: Optimization of Energy Conversion Efficiency for Wearable Harvesting. *Review of Applied Science and Technology*, *3*(03), 31–72. https://doi.org/10.63125/w7q9cs55

[3]. Abeykoon, C., Kelly, A. L., Brown, E. C., & Coates, P. D. (2016). The effect of materials, process settings and screw geometry on energy consumption and melt temperature in single screw extrusion. *Applied Energy*, *180*, 880-894. https://doi.org/10.1016/j.apenergy.2016.07.014

[4]. Adnan, S., & Iftekhar, A. (2023). Predicting Cost Variance in Digital Transformation Projects Through Ensemble Learning and Project Performance Analytics. *International Journal of Scientific Interdisciplinary Research*, *13*(10), 01–36. https://doi.org/10.63125/j18hxs51

[5]. Ahmed, H. C. H. R. (2024). Machine Learning Enhanced Demand Forecasting and Portfolio Analytics for Scalable Growth Management in Digital Logistics Operations. *American Journal of Advanced Technology and Engineering Solutions*, *4*(02), 33-81. https://doi.org/10.63125/5xq3nd53

[6]. Ahmed, H. C. H. R. (2026). An Artificial Intelligence Integrated IT Management Framework for Analytics-Driven Operational Decision-Making in U.S. Supply Chain and Logistics Systems. *American Journal of Interdisciplinary Studies*, *16*(06), 01-37. https://doi.org/10.63125/b5hgg259

[7]. Ahmed, H. C. H. R., & Nuzhat Sadia, P. (2023). A Quantitative Assessment of CRM Analytics and KPI Dashboard Design on Enterprise Revenue Conversion in Emerging Market Logistics Platforms. *American Journal of Data Science and Analytics*, *4*(09), 50-95. https://doi.org/10.63125/315bge15

[8]. Amirkhosravi, M., Yue, L., Ju, T., & Manas-Zloczower, I. (2021). Designing thermal annealing to control mechanical performance of thermoplastic polyurethane elastomers. *Polymer*, *214*, 123254. https://doi.org/10.1016/j.polymer.2020.123254

[9]. Andersson, M. G., Städler, R., Hagstrand, P.-O., Gkourmpis, T., Andersson, M. R., & Müller, C. (2018). Influence of molecular weight on the creep resistance of almost molten polyethylene blends. *Macromolecular Chemistry and Physics*, *219*(3), 1700072. https://doi.org/10.1002/macp.201700072

[10]. Andraju, N., Curtzwiler, G. W., Ji, Y., Kozliak, E., & Ranganathan, P. (2022). Machine-learning-based predictions of polymer and postconsumer recycled polymer properties: A comprehensive review. *ACS Applied Materials & Interfaces*, *14*(38), 42771-42790. https://doi.org/10.1021/acsami.2c08301

[11]. Asheke, M. (2023). Machine Learning–Based Predictive Quality Modeling for Defect Detection and Process Optimization in Advanced Manufacturing Systems. *Review of Applied Science and Technology*, *13*(12), 01–49. https://doi.org/10.63125/thy73b16

[12]. Asheke, M. (2024). Digital Twin and Industrial Internet of Things–Enabled Predictive Maintenance for Reliability Enhancement in Smart Manufacturing Systems. *International Journal of Scientific Interdisciplinary Research*, *5*(2), 792–838. https://doi.org/10.63125/jgrdqd62

[13]. Ashik, M., & Shabbir, A. (2022). Digital Twin-Enabled Predictive Maintenance for Rotating and Static Equipment: Bridging FEA-Based Failure Analysis with Real-Time Asset Health Monitoring in Energy and Power Facilities. *International Journal of Scientific Interdisciplinary Research*, *12*(05), 01–37. https://doi.org/10.63125/0qaysz49

[14]. Ashrafuzzaman, M. (2024). The impact of cloud-based management information systems on hrm efficiency: an analysis of small and medium-sized enterprises (SMES). *Academic Journal on Artificial Intelligence, Machine Learning, Data Science and Management Information Systems*, *1*(01), 40-56. https://doi.org/10.69593/ajaimldsmis.v1i01.124

[15]. Bonfanti, A., Kaplan, J. L., Charras, G., & Kabla, A. (2020). Fractional viscoelastic models for power-law materials. *Soft Matter*, *16*(26), 6002-6020. https://doi.org/10.1039/d0sm00354a

[16]. Chen, G., Shen, Z., Iyer, A., Ghumman, U. F., Tang, S., Bi, J., Chen, W., & Li, Y. (2020). Machine-learning-assisted de novo design of organic molecules and polymers: Opportunities and challenges. *Polymers*, *12*(1), 163. https://doi.org/10.3390/polym12010163

[17]. Chen, L., Kim, C., Batra, R., Lightstone, J. P., Wu, C., Li, Z., Deshmukh, A. A., Wang, Y., Tran, H. D., Vashishta, P., Sotzing, G. A., Cao, Y., & Ramprasad, R. (2020). Frequency-dependent dielectric constant prediction of polymers using machine learning. *npj Computational Materials*, *6*, 61. https://doi.org/10.1038/s41524-020-0333-6

[18]. Chen, L., Pilania, G., Batra, R., Huan, T. D., Kim, C., Kuenneth, C., & Ramprasad, R. (2021). Polymer informatics: Current status and critical next steps. *Materials Science and Engineering: R: Reports*, *144*, 100595. https://doi.org/10.1016/j.mser.2020.100595

[19]. Chen, Z., Wu, Y., Xie, Y., Sattari, K., & Lin, J. (2024). Physics-informed machine learning enabled virtual experimentation for 3D printed thermoplastic. *Materials Horizons*, *11*(23), 6028-6039. https://doi.org/10.1039/d4mh01022a

[20]. Chevali, V. S., Dean, D. R., & Janowski, G. M. (2009). Flexural creep behavior of discontinuous thermoplastic composites: Non-linear viscoelastic modeling and time-temperature-stress superposition. *Composites Part A: Applied Science and Manufacturing*, *40*(6-7), 870-877. https://doi.org/10.1016/j.compositesa.2009.04.012

[21]. Chevali, V. S., & Ulven, C. A. (2012). Effect of extrusion screw speed on biocomposite thermo-mechanical properties. *International Journal of Sustainable Engineering*, *5*(1), 38-46. https://doi.org/10.1080/19397038.2010.547625

[22]. Chew, A. K., Sender, M., Kaplan, Z., Chandrasekaran, A., Chief Elk, J., Browning, A. R., Kwak, H. S., Halls, M. D., & Afzal, M. A. F. (2024). Advancing material property prediction: Using physics-informed machine learning models for viscosity. *Journal of Cheminformatics*, *16*, 31. https://doi.org/10.1186/s13321-024-00820-5

[23]. Domenech, T., Peuvrel-Disdier, E., & Vergnes, B. (2013). The importance of specific mechanical energy during twin screw extrusion of organoclay based polypropylene nanocomposites. *Composites Science and Technology*, *75*, 7-14. https://doi.org/10.1016/j.compscitech.2012.11.016

[24]. Dorleans, V., Delille, R., Notta-Cuvier, D., Lauro, F., & Michau, E. (2021). Time-temperature superposition in viscoelasticity and viscoplasticity for thermoplastics. *Polymer Testing*, *101*, 107287. https://doi.org/10.1016/j.polymertesting.2021.107287

[25]. Endo, V. T., & de Carvalho Pereira, J. C. (2017). Linear orthotropic viscoelasticity model for fiber reinforced thermoplastic material based on Prony series. *Mechanics of Time-Dependent Materials*, *21*(2), 199-221. https://doi.org/10.1007/s11043-016-9326-8

[26]. Ganvir, V., Gautham, B. P., Pol, H., Bhamla, M. S., Sclesi, L., Thaokar, R., Lele, A. K., & Mackley, M. (2011). Extrudate swell of linear and branched polyethylenes: ALE simulations and comparison with experiments. *Journal of Non-Newtonian Fluid Mechanics*, *166*(1-2), 12-24. https://doi.org/10.1016/j.jnnfm.2010.10.001

[27]. Gaspar-Cunha, A., Covas, J. A., & Sikora, J. (2022). Optimization of polymer processing: A review (Part I: Extrusion). *Materials*, *15*(1), 384. https://doi.org/10.3390/ma15010384

[28]. Gazi Yeasin, A. (2023). Impact of Accessibility-First Design Systems on WCAG 2.1 Compliance and Inclusive User Experience in Enterprise Software Platforms: A Mixed-Methods Evaluation. *Review of Applied Science and Technology*, *13*(07), 01–49. https://doi.org/10.63125/nxh4gp19

[29]. Ghosh, A. (2024). Towards physics-informed explainable machine learning and causal models for materials research. *Computational Materials Science*, *233*, 112740. https://doi.org/10.1016/j.commatsci.2023.112740

[30]. Han, B., Yin, D., & Gao, Y. (2023). Analysis of the variable-order fractional viscoelastic modeling with application to polymer materials. *Polymers for Advanced Technologies*, *34*(8), 2707-2720. https://doi.org/10.1002/pat.6084

[31]. Hyvarinen, M., Jabeen, R., & Karki, T. (2020). The modelling of extrusion processes for polymers: A review. *Polymers*, *12*(6), 1306. https://doi.org/10.3390/polym12061306

[32]. Jahanara, A. (2025). AI-Enabled Workforce Management: Its Impact on Employee Burnout, Staffing Efficiency, and Organizational Performance in Healthcare. *Review of Applied Science and Technology*, *4*(04), 247–295. https://doi.org/10.63125/5617ff74

[33]. Jahanara, A. (2026). Impact of Artificial Intelligence on Operational Efficiency and Cost Reduction in U.S. Healthcare Organizations. *American Journal of Interdisciplinary Studies*, *7*(02), 225-276. https://doi.org/10.63125/3p24ma43

[34]. Jahanara, A., & Mst Kaniz, F. (2023). Demand Variability and Capacity Planning in Home and Community-Based Services: A Decision-Analytic Framework for Health Services Managers. *American Journal of Data Science and Analytics*, *4*(09), 01-49. https://doi.org/10.63125/3y62vr16

[35]. Jannatul, F. (2025). Spinal Cord Injury and Neurorehabilitation Deep Learning–Based Prediction of Functional Recovery Trajectories After Traumatic Spinal Cord Injury. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 2865–2922. https://doi.org/10.63125/m738bh82

[36]. Jannatul, F. (2026). Predicting Falls and Mobility Decline Among Older Adults Using Longitudinal Functional Data and Ensemble Machine Learning. *International Journal of Scientific Interdisciplinary Research*, *7*(1), 581–631. https://doi.org/10.63125/56hans40

[37]. Karniadakis, G. E., Kevrekidis, I. G., Lu, L., Perdikaris, P., Wang, S., & Yang, L. (2021). Physics-informed machine learning. *Nature Reviews Physics*, *3*, 422-440. https://doi.org/10.1038/s42254-021-00314-5

[38]. Karpatne, A., Atluri, G., Faghmous, J. H., Steinbach, M., Banerjee, A., Ganguly, A., Shekhar, S., Samatova, N., & Kumar, V. (2017). Theory-guided data science: A new paradigm for scientific discovery from data. *IEEE Transactions on Knowledge and Data Engineering*, *29*(10), 2318-2331. https://doi.org/10.1109/tkde.2017.2720168

[39]. Kazi Mohammad Khalid, A. (2026). A Systematic Review of GeoAI and Deep Learning for Automated Road Infrastructure Damage Detection Using Satellite Imagery. *American Journal of Data Science and Analytics*, *7*(03), 208-255. https://doi.org/10.63125/77cy0h19

[40]. Kazi Rakib Hasan, S., & Adnan, S. (2022). Quantitative Assessment of Machine Learning-Based Schedule Risk Prediction for Reducing Delays in Complex Technology Projects. *Review of Applied Science and Technology*, *1*(04), 464–501. https://doi.org/10.63125/dn8nkm85

[41]. Kim, C., Chandrasekaran, A., Huan, T. D., Das, D., & Ramprasad, R. (2018). Polymer Genome: A data-powered polymer informatics platform for property predictions. *The Journal of Physical Chemistry C*, *122*(31), 17575-17585. https://doi.org/10.1021/acs.jpcc.8b02913

[42]. Kolařík, J., & Pegoretti, A. (2006). Non-linear tensile creep of polypropylene: Time-strain superposition and creep prediction. *Polymer*, *47*(1), 346-356. https://doi.org/10.1016/j.polymer.2005.11.013

[43]. Krauklis, A. E., Akulichev, A. G., Gagani, A. I., & Echtermeyer, A. T. (2019). Time-temperature-plasticization superposition principle: Predicting creep of a plasticized epoxy. *Polymers*, *11*(11), 1848. https://doi.org/10.3390/polym11111848

[44]. Kuenneth, C., Rajan, A. C., Tran, H., Chen, L., Kim, C., & Ramprasad, R. (2021). Polymer informatics with multi-task learning. *Patterns*, *2*(4), 100238. https://doi.org/10.1016/j.patter.2021.100238

[45]. Lei, D., Liang, Y., & Xiao, R. (2018). A fractional model with parallel fractional Maxwell elements for amorphous thermoplastics. *Physica A: Statistical Mechanics and Its Applications*, *490*, 465-475. https://doi.org/10.1016/j.physa.2017.08.037

[46]. Lobato, H., Cernuda, C., Zulueta, K., Arriaga, A., Matxain, J. M., & Burgoa, A. (2024). Prediction of long-term creep modulus of thermoplastics using brief tests and interpretable machine learning. *International Journal of Solids and Structures*, *304*, 113014. https://doi.org/10.1016/j.ijsolstr.2024.113014

[47]. Luo, W., Wang, C., Hu, X., & Yang, T. (2012). Long-term creep assessment of viscoelastic polymer by time-temperature-stress superposition. *Acta Mechanica Solida Sinica*, *25*(6), 571-578. https://doi.org/10.1016/s0894-9166(12)60052-4

[48]. Ma, H., Li, T., Pan, B., Li, J., Jiang, S., Peng, X., & Jing, L. (2022). Tensile behaviour of isotactic polypropylene with different crystallinities and service temperatures. *Polymer Testing*, *116*, 107756. https://doi.org/10.1016/j.polymertesting.2022.107756

[49]. Mahbubul, I., Mahmudul, I., Shifa, T., Mahfuza, T., & Shima Ali, S. (2022). Exploring The Potential of Visual Narratives and Interactive Gamified Communication Systems to Prevent Disease, Counter Health Misinformation, And Strengthen Public Trust in Low-Literacy Communities: A Literature Review. *American Journal of Interdisciplinary Studies*, *3*(02), 165-220. https://doi.org/10.63125/zmqs4n64

[50]. Mahmoudabadbozchelou, M., & Jamali, S. (2021). Rheology-informed neural networks (RhINNs) for forward and inverse metamodelling of complex fluids. *Scientific Reports*, *11*, 12015. https://doi.org/10.1038/s41598-021-91518-3

[51]. Maishar Mostari, Z. (2025). Impact of Deep Learning on Real-Time Network Intrusion Detection: A Quantitative Evaluation Using Benchmark Datasets. *Review of Applied Science and Technology*, *4*(04), 296–338. https://doi.org/10.63125/tnaksd40

[52]. Mamalis, A. G., Spentzas, K. N., Kouzilos, G., Theodorakopoulos, I., & Pantelelis, N. G. (2010). On the high-density polyethylene extrusion: Numerical, analytical and experimental modeling. *Advances in Polymer Technology*, *29*(3), 173-184. https://doi.org/10.1002/adv.20185

[53]. Mannodi-Kanakkithodi, A., Chandrasekaran, A., Kim, C., Huan, T. D., Pilania, G., Botu, V., & Ramprasad, R. (2018). Scoping the polymer genome: A roadmap for rational polymer dielectrics design and beyond. *Materials Today*, *21*(7), 785-796. https://doi.org/10.1016/j.mattod.2017.11.021

[54]. Martin, T. B., & Audus, D. J. (2023). Emerging trends in machine learning: A polymer perspective. *ACS Polymers Au*, *3*(3), 239-258. https://doi.org/10.1021/acspolymersau.2c00053

[55]. Mashfiqur, R. (2025). Multivariate Time-Series Forecasting of Working Capital Requirements for Improving Cash-Flow Stability in Export-Oriented Manufacturing. *American Journal of Data Science and Analytics*, *6*(12), 217-249. https://doi.org/10.63125/ty3dtt46

[56]. Mashfiqur, R. (2026). Explainable Artificial Intelligence for Supplier Cost-Risk Assessment and Margin Optimization in Global Manufacturing Supply Chains. *American Journal of Interdisciplinary Studies*, *16*(08), 01-37. https://doi.org/10.63125/np6bw920

[57]. Mashfiqur, R., & Md, A. (2022). Monte Carlo Simulation and Stochastic Cash-Flow Modeling for Reducing Liquidity Risk in Project-Based Enterprises. *International Journal of Scientific Interdisciplinary Research*, *1*(01), 382–431. https://doi.org/10.63125/zf3fwv21

[58]. Mashiat, N. (2024). Reducing Telecommunications Service Interruptions Through Predictive Root-Cause Analytics of Multivariate System Telemetry. *International Journal of Scientific Interdisciplinary Research*, *14*(11), 01-37. https://doi.org/10.63125/nqjh0c29

[59]. Mashiat, N. (2025). Improving Enterprise Data Integrity Through Automated Validation and Schema-Drift Detection in Large-Scale Data Integration Systems. *Review of Applied Science and Technology*, *4*(02), 889–934. https://doi.org/10.63125/21zzkk04

[60]. Mashiat, N. (2026). Accelerating Incident Diagnosis and Service Recovery Through Generative AI-Assisted Failure Intelligence in Critical Digital Infrastructure. *American Journal of Data Science and Analytics*, *7*(06), 702-740. https://doi.org/10.63125/61etqg30

[61]. Mashiat, N., & Md Anisur Rahman, M. (2022). Machine Learning Approaches to Credit Risk Scoring and Default Prediction in Small-Business Lending: Empirical Evidence from Lending Portfolio Data. *American Journal of Data Science and Analytics*, *3*(06), 137-182. https://doi.org/10.63125/j256rs96

[62]. Md, A., & Gazi Yeasin, A. (2022). Machine Learning Enhanced Spatial-Data Workflow Redesign: A Quantitative Evaluation of Task Success and Operational Cost Reduction in Enterprise LiDAR Platforms. *American Journal of Data Science and Analytics*, *3*(06), 80-136. https://doi.org/10.63125/0den7c02

[63]. Md Anisur Rahman, M. (2023). Development of AI-Driven Business Intelligence Frameworks for Financial Risk and Liquidity Monitoring in Real Time. *International Journal of Scientific Interdisciplinary Research*, *4*(2), 152–203. https://doi.org/10.63125/jm55ca64

[64]. Md Arif Uz, Z., Sharmin, S., & Md Abdur, R. (2025). Factors Influencing Behavioural Intention to Use he Innovative Open And Distance Learning Systems With The Role Of Continuance Intention. *American Journal of Scholarly Research and Innovation*, *4*(01), 202-220. https://doi.org/10.63125/pbjxp014

[65]. Md Ashfaq, S., & Abdullah Mohammad, S. (2022). CNT/PANI Composite Electrodes for Flexible Fiber-Shaped Dye-Sensitized Solar Cells: Synthesis, Characterization, and Photovoltaic Performance. *American Journal of Interdisciplinary Studies*, *3*(02), 221-274. https://doi.org/10.63125/m334mf41

[66]. Md Asif Ali Sheak, A., & Tahmedur, R. (2023). A Data-Driven Framework for Engineering Project Risk Assessment Under Schedule and Cost Uncertainty. *International Journal of Scientific Interdisciplinary Research*, *4*(2), 204–251. https://doi.org/10.63125/kq4zzh16

[67]. Md Kaium, H. (2023). A GIS-Based Multi-Criteria Decision-Support and Land-Suitability Optimization Framework for Climate-Resilient Urban and Regional Planning. *American Journal of Data Science and Analytics*, *4*(06), 43–103. https://doi.org/10.63125/wvq0sx87

[68]. Md Kaium, H. (2024). Machine Learning Enhanced GIS And AHP Modeling for High-Resolution Flood-Susceptibility Prediction, Vulnerability Assessment, and Risk Classification. *Review of Applied Science and Technology*, *3*(02), 92–140. https://doi.org/10.63125/fz8hv245

[69]. Md Kaium, H. (2025). Integrating Artificial Intelligence, Semantic Indoor Geospatial Modeling, And Network-Based Routing for High-Precision NG911 Emergency Location Intelligence. *International Journal of Scientific Interdisciplinary Research*, *6*(1), 616–670. https://doi.org/10.63125/5hc1xx56

[70]. Md Kaium, H. (2026). An Artificial Intelligence Integrated Geospatial Decision-Support Framework for Scenario-Based Climate-Adaptive Land-Use Optimization and Environmental Risk Reduction. *American Journal of Data Science and Analytics*, *7*(06), 425-483. https://doi.org/10.63125/nyc7sh45

[71]. Md Mahamud Pervaz, P. (2023). Integration of MES, SAP, And PI Historian Platforms for Real-Time Industrial Asset Performance Management. *Review of Applied Science and Technology*, *2*(04), 393–445. https://doi.org/10.63125/9ebtas97

[72]. Md Mahamud Pervaz, P. (2025). Development of a CMMS-Integrated Predictive Maintenance Framework for Industrial PLC and Drive Systems. *American Journal of Scholarly Research and Innovation*, *4*(01), 894–942. https://doi.org/10.63125/j33gtf31

[73]. Md Mahamud Pervaz, P. (2026). Implementation of an OSHA-Compliant Lockout/Tagout and Arc-Flash Hazard Mitigation Framework for U.S. Industrial Maintenance Operations. *American Journal of Interdisciplinary Studies*, *7*(02), 73-119. https://doi.org/10.63125/8ky04n07

[74]. Meijer, H. E. H., & Govaert, L. E. (2005). Mechanical performance of polymer systems: The relation between structure and properties. *Progress in Polymer Science*, *30*(8-9), 915-938. https://doi.org/10.1016/j.progpolymsci.2005.06.009

[75]. Mohammad Badrul, A., & Md. Mominul, H. (2023). Machine Learning–Based Assessment of Environmental and Public Health Risks in Sewerage Sludge Management Systems. *American Journal of Advanced Technology and Engineering Solutions*, *3*(02), 33-77. https://doi.org/10.63125/y3yfxa92

[76]. Molla Al Rakib, H., & Mohammad Towhidul, I. (2023). Cyber-Resilient Marketing Intelligence Systems for Fraud Detection and Data Integrity in Digital Campaigns. *American Journal of Scholarly Research and Innovation*, *2*(02), 485–518. https://doi.org/10.63125/b53pgr11

[77]. Mst Kaniz, F., & Jahanara, A. (2022). Lean Six Sigma Implementation in Home Health Administrative Operations: A DMAIC Case Study of Managerial Workflow Redesign and Error Reduction. *International Journal of Scientific Interdisciplinary Research*, *12*(04), 01–60. https://doi.org/10.63125/xchca204

[78]. Mst Shamima, A. (2026). Enhancing Financial Accountability and Cost Control in North American Outpatient Clinics Through Data Science: A Mixed-Methods Healthcare Administration Study. *American Journal of Data Science and Analytics*, *7*(05), 01-41. https://doi.org/10.63125/wksgy749

[79]. Mukut Kanti, B. (2023). Importance of the Sustainable growth in the Testing, Inspection and Certification (TIC) industries through AI tools and techniques. *Review of Applied Science and Technology*, *13*(07), 50–75. https://doi.org/10.63125/0aagev30

[80]. Mukut Kanti, B. (2024). AI-Enabled Predictive Asset Integrity Monitoring for Industrial Equipment in Oil & Gas and Energy Sector Facilities. *International Journal of Scientific Interdisciplinary Research*, *5*(2), 746–791. https://doi.org/10.63125/3mjcah04

[81]. Mukut Kanti, B. (2026). Digital-Twin And IOT-Based Condition Monitoring for Rotating Machinery and Process Equipment in Petrochemical and Industrial Environments. *American Journal of Scholarly Research and Innovation*, *5*(01), 382–428. https://doi.org/10.63125/mwdnjv55

[82]. Munir, N., McMorrow, R., Mulrennan, K., Whitaker, D., McLoone, S., Kellomaki, M., Talvitie, E., Lyyra, I., & McAfee, M. (2023). Interpretable machine learning methods for monitoring polymer degradation in extrusion of polylactic acid. *Polymers*, *15*(17), 3566. https://doi.org/10.3390/polym15173566

[83]. Mysona, J. A., Nealey, P. F., & de Pablo, J. J. (2024). Machine learning models and dimensionality reduction for prediction of polymer properties. *Macromolecules*, *57*(5), 1988-1997. https://doi.org/10.1021/acs.macromol.3c02401

[84]. Nikitine, C., Rodier, E., Sauceau, M., & Fages, J. (2009). Residence time distribution of a pharmaceutical grade polymer melt in a single screw extrusion process. *Chemical Engineering Research and Design*, *87*(6), 809-816. https://doi.org/10.1016/j.cherd.2008.10.008

[85]. Nishat, J. (2023). Communicable Disease Prevention in a Post-Pandemic Era: A Global Review of Public Health Education, Surveillance, and Community-Level Interventions. *International Journal of Scientific Interdisciplinary Research*, *4*(4), 630–678. https://doi.org/10.63125/mnqefj36

[86]. Nuzhat Sadia, P. (2023). A Multi-Criteria Decision-Support Framework For ERP-Based Business Process Optimization in Mid-Sized Manufacturing Enterprises. *American Journal of Scholarly Research and Innovation*, *2*(02), 519–573. https://doi.org/10.63125/j58k5d55

[87]. Palash Chandra, D. (2025). Advanced Composite and Geopolymer Materials for Durable Water Supply and Sanitation Infrastructure: Performance, Sustainability, and Lifecycle Assessment. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 1887–1921. https://doi.org/10.63125/z64akr77

[88]. Patra, T. K. (2022). Data-driven methods for accelerating polymer design. *ACS Polymers Au*, *2*(1), 8-26. https://doi.org/10.1021/acspolymersau.1c00035

[89]. Pilz, G., Wurzer, S., Morak, M., & Pinter, G. (2022). Assessment of the stepped isothermal method for accelerated creep testing of high-density polyethylene. *Mechanics of Time-Dependent Materials*, *26*, 775-790. https://doi.org/10.1007/s11043-021-09512-1

[90]. Raissi, M., Perdikaris, P., & Karniadakis, G. E. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. *Journal of Computational Physics*, *378*, 686-707. https://doi.org/10.1016/j.jcp.2018.10.045

[91]. Ranade, A., Nayak, K., Fairbrother, D., & D'Souza, N. A. (2005). Maleated and non-maleated polyethylene-montmorillonite layered silicate blown films: Creep, dispersion and crystallinity. *Polymer*, *46*(18), 7323-7333. https://doi.org/10.1016/j.polymer.2005.04.085

[92]. Raquez, J.-M., Narayan, R., & Dubois, P. (2008). Recent advances in reactive extrusion processing of biodegradable polymer-based compositions. *Macromolecular Materials and Engineering*, *293*(6), 447-470. https://doi.org/10.1002/mame.200700395

[93]. Reyes, B., Howard, A. A., Perdikaris, P., & Tartakovsky, A. M. (2021). Learning unknown physics of non-Newtonian fluids. *Physical Review Fluids*, *6*(7), 073301. https://doi.org/10.1103/PhysRevFluids.6.073301

[94]. Risha, A., & Mst Shurovi, A. (2023). Cloud-Based Accounting Systems and Cybersecurity Frameworks for Financial Data Protection in Emerging Economies: A Meta-Analysis. *International Journal of Business and Economics Insights*, *3*(4), 26–64. https://doi.org/10.63125/zb0h3n85

[95]. Rony, S., & Md, A. (2026). Multi-Agency Coordination in Sustained Healthcare Supply Shortages: Lessons from Covid-19, Drug Shortages, and Critical Medical Supply Disruptions. *American Journal of Data Science and Analytics*, *7*(01), 181-221. https://doi.org/10.63125/5v6t8515

[96]. Sadia, Z., & Maishar Mostari, Z. (2022). The Impact of Interactive Dashboard Visualization on Data-Driven Decision Making in Financial Services: A Qualitative Evaluation. *International Journal of Scientific Interdisciplinary Research*, *12*(03), 01–35. https://doi.org/10.63125/3jstsv75

[97]. Schmid, F. (2023). Understanding and modeling polymers: The challenge of multiple scales. *ACS Polymers Au*, *3*(1), 28-58. https://doi.org/10.1021/acspolymersau.2c00049

[98]. Schmidt, R. F., Winter, H. H., & Gradzielski, M. (2024). Generalized vs. fractional: A comparative analysis of Maxwell models applied to entangled polymer solutions. *Soft Matter*, *20*(39), 7914-7925. https://doi.org/10.1039/d4sm00749b

[99]. Shaiful, M., Anisur, R., & Md, A. (2022). A Systematic Literature Review on the Role of Digital Health Twins in Preventive Healthcare For Personal and Corporate Wellbeing. *American Journal of Interdisciplinary Studies*, *3*(04), 1-31. https://doi.org/10.63125/negjw373

[100]. Shimakawa, H., Kumada, A., & Sato, M. (2024). Prevention of leakage in machine learning prediction for polymer composite properties. *Journal of Chemical Information and Modeling*, *64*(9), 3621-3629. https://doi.org/10.1021/acs.jcim.3c01894

[101]. Sikora, J. W. (2008). Review: Increasing the efficiency of the extrusion process. *Polymer Engineering & Science*, *48*(9), 1678-1682. https://doi.org/10.1002/pen.20998

[102]. Stabak, D., & Md Shahid, N. (2022). Empirical Assessment of Uncertainty-Aware Real-Time Decision-Making for Reliable and Resilient Cyber-Physical Systems. *International Journal of Scientific Interdisciplinary Research*, *1*(01), 432–477. https://doi.org/10.63125/q3r4kk16

[103]. Stabak, D., & Md Siam, T. (2023). Real-Time Edge Computing for Cyber-Physical Systems: A Meta-Analysis of Energy Efficiency and Fault Tolerance. *American Journal of Scholarly Research and Innovation*, *13*(06), 01–44. https://doi.org/10.63125/g9c9cp41

[104]. Syed Feroz, A. (2023). Quality-Management Systems for Resilient Energy Infrastructure Fabrication. *International Journal of Scientific Interdisciplinary Research*, *13*(10), 37–91. https://doi.org/10.63125/mbhhrm88

[105]. Syed Feroz, A. (2024). AI-Assisted NDT Analytics for Early Crack Detection in Energy-Infrastructure Pressure Vessels Using Advanced Manufacturing Data. *Review of Applied Science and Technology*, *14*(07), 01-52. https://doi.org/10.63125/8bdqs538

[106]. Syed Feroz, A. (2025). Intelligent Process Monitoring for Enhancing Weld Integrity and Reliability in Advanced Manufacturing of LPG Energy Infrastructure. *American Journal of Interdisciplinary Studies*, *6*(3), 394-441. https://doi.org/10.63125/p3b5mb44

[107]. Syed Feroz, A., & Md Mahamud Pervaz, P. (2022). Root-Cause Analysis and FMEA-Driven Reliability Improvement in Gas Production Facilities: A Multi-Year Empirical Study. *International Journal of Scientific Interdisciplinary Research*, *12*(10), 01–53. https://doi.org/10.63125/70msp878

[108]. Tahmedur, R., & Rifat, C. (2023). Critical Path Analysis and Resource-Leveling Optimization for Multi-Project Engineering Portfolios. *American Journal of Interdisciplinary Studies*, *13*(12), 01-47. https://doi.org/10.63125/8eqnea46

[109]. Thiry, J., Krier, F., & Evrard, B. (2015). A review of pharmaceutical extrusion: Critical process parameters and scaling-up. *International Journal of Pharmaceutics*, *479*(1), 227-240. https://doi.org/10.1016/j.ijpharm.2014.12.036

[110]. Thyashan, N., Perera, Y. S., Xiao, R., & Abeykoon, C. (2024). Investigation of the effect of materials and processing conditions in twin-screw extrusion. *International Journal of Lightweight Materials and Manufacture*, *7*(3), 353-361. https://doi.org/10.1016/j.ijlmm.2023.09.003

[111]. Tran, H. D., Kim, C., Chen, L., Chandrasekaran, A., Batra, R., Venkatram, S., Kamal, D., Lightstone, J. P., Gurnani, R., Shetty, P., Ramprasad, M., Laws, J., Shelton, M., & Ramprasad, R. (2020). Machine-learning predictions of polymer properties with Polymer Genome. *Journal of Applied Physics*, *128*(17), 171104. https://doi.org/10.1063/5.0023759

[112]. Tscharnuter, D., & Muliana, A. (2013). Nonlinear response of viscoelastic polyoxymethylene (POM) at elevated temperatures. *Polymer*, *54*(3), 1208-1217. https://doi.org/10.1016/j.polymer.2012.12.043

[113]. Uddin, H. M. M., & Risha, A. (2024). Hybrid Cloud Security and Compliance in U.S. Enterprises: Addressing Data Privacy Risks and Governance Challenges. *American Journal of Scholarly Research and Innovation*, *3*(01), 153–197. https://doi.org/10.63125/qcy0cj46

[114]. Vera-Sorroche, J., Kelly, A. L., Brown, E. C., Gough, T., Abeykoon, C., Coates, P. D., Deng, J., Li, K., Harkin-Jones, E., & Price, M. (2014). The effect of melt viscosity on thermal efficiency for single screw extrusion of HDPE. *Chemical Engineering Research and Design*, *92*(11), 2404-2412. https://doi.org/10.1016/j.cherd.2013.12.025

[115]. Virag, A. D., & Molnar, K. (2024). Modelling the time-dependent mechanical properties of thermoplastic and thermosetting polymers with Gumbel distribution functions. *Polymer*, *312*, 127642. https://doi.org/10.1016/j.polymer.2024.127642

[116]. Wilczynski, K., Nastaj, A., Lewandowski, A., Wilczynski, K. J., & Buziak, K. (2019). Fundamentals of global modeling for polymer extrusion. *Polymers*, *11*(12), 2106. https://doi.org/10.3390/polym11122106

[117]. Wu, S., Kondo, Y., Kakimoto, M.-A., Yang, B., Yamada, H., Kuwajima, I., Lambard, G., Hongo, K., Xu, Y., Shiomi, J., Schick, C., Morikawa, J., & Yoshida, R. (2019). Machine-learning-assisted discovery of polymers with high thermal conductivity using a molecular design algorithm. *npj Computational Materials*, *5*, 66. https://doi.org/10.1038/s41524-019-0203-2

[118]. Xu, H., & Jiang, X. (2017). Creep constitutive models for viscoelastic materials based on fractional derivatives. *Computers & Mathematics with Applications*, *73*(6), 1377-1384. https://doi.org/10.1016/j.camwa.2016.05.002

[119]. Yang, C., Ma, W., Zhong, J., & Zhang, Z. (2021). Comparative study of machine learning approaches for predicting creep behavior of polyurethane elastomer. *Polymers*, *13*(11), 1768. https://doi.org/10.3390/polym13111768

[120]. Yeh, I.-C., Andzelm, J. W., & Rutledge, G. C. (2015). Mechanical and structural characterization of semicrystalline polyethylene under tensile deformation by molecular dynamics simulations. *Macromolecules*, *48*(12), 4228-4239. https://doi.org/10.1021/acs.macromol.5b00697

[121]. Yuan, S., & Sakai, T. (2024). Investigating the influence of free volume and temperature on time-temperature superposition principle by MD simulation. *Mechanical Engineering Journal*, *11*(6), 24-00242. https://doi.org/10.1299/mej.24-00242