Journal of Theoretical and Applied Information Technology
31st January 2026. Vol.104. No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

A COMPUTATIONALLY-STRUCTURED FRAMEWORK FOR GENERALIZABLE AND EXPLAINABLE AI IN INJECTION MOLDING: INTEGRATING DATA STANDARDIZATION, TRANSFER LEARNING, AND EDGE DEPLOYMENT

MOHAMMED HDID [1], HAKIM JEBARI [2], HASSAN SAMADI [3]

[1,2,3] Laboratory of Information and Communication Technologies (LABTIC), University Abdelmalek Essaâdi, Tangier, Morocco
[2] Artificial Intelligence, Data Science, and Innovation Research Team, LaBEL, National School of Architecture of Tetouan
[2] Innovative Systems Engineering Laboratory, University Abdelmalek Essaâdi, Morocco
[1] hdid.mohammed@gmail.com, [2] hjebari1@yahoo.fr, [3] hsamadi@uae.ac.ma

ABSTRACT

The emergence of Artificial Intelligence (AI) and Machine Learning (ML) is now the key element of modern manufacturing, but the majority of the models applied in injection molding are domain-specific and cannot be generalized to other machines, materials, or process conditions. The given paper deals with this computing problem by developing a structured literature review devoted to the issue of the generalization and transferability of industrial AI systems. Based on this discussion, a conceptual framework of 5 steps is put forward to formalize the way in which cross-domain robustness may be attained based on fundamental computing systems like data normalization, feature relevance control, regularization, domain adaptation, and explainable modeling. The stages are all based on the latest developments in AI, the introduction of digital-twin, and the integration of hybrid edge-cloud architecture. The framework suggested opens up a hypothetical basis of constructing domain resistant and intelligible artificial pipelines, that links machine particular learning with scalable and transferable intelligence. This effort to coordinate the data of industrial processes with the principles of reproducibility and generalization in computing leads to the further development of both AI methodology and practical use of smart manufacturing in the direction of the reliable and cross-domain automatization.

Keywords: *Plastic Injection Molding, Machine Learning (ML), Artificial Intelligence (AI), Process Optimization, Production Efficiency, Feature Normalization, Defect Detection and Prediction, Explainable AI (XAI), Predictive Maintenance, Digital Twin.*

1. INTRODUCTION

Machine learning (ML) and artificial intelligence (AI) now play a crucial role in the contemporary manufacturing process, as it stimulates the progress of quality prediction, process optimization, and energy efficiency. The AI models are becoming more popular in injection molding to predict the defects of parts, optimize processing conditions, and minimize waste of the material. These methods have a high potential of enhancing uniformity and lessening human reliance in elaborate production settings. Nevertheless, these successes are not enough without a long-standing limitation, which is that the majority of AI solutions can be used reliably only when trained on a very small range of data [1], [2], [3], [4].

Despite the proven efficacy of AI in injection molding, existing models are largely domain-specific and fail to generalize across different machines, materials, or process conditions. This limitation hinders scalable and cost-effective industrial deployment. To address this, the paper proposes a structured 5-step conceptual framework integrating data normalization, feature selection, transfer learning, explainability, and edge deployment. The framework is designed to bridge the gap between isolated high-accuracy models and scalable, trustworthy industrial AI systems.

One of the most prevailing manufacturing processes in the world is injection molding, whereby the world market is estimated to be USD 403.85 billion in 2024 and USD 561.58 billion in

2032 at a CAGR of 4.22% [5]. The industry is also driven by increasing demand in the automotive, electronic and packaging industry and more so the pharmaceutical manufacturing industry which is worth USD 632.71 billion in 2025 [6]. This fact supports the fact that its presence in all these industries makes the concern of providing process efficiency, product consistency, and sustainability due to digital transformation an emergency [7], [8].

This is what is referred to as the generalizability problem where when models are trained on data of a particular machine, mold or material they do not prove accurate when used in other conditions. As a practical matter, differences in sensor calibration, machine dynamics, resin rheology, and environmental conditions introduce domain shifts that are even hard to handle with highly sophisticated models [4], [9]. As a result, AI systems that seem to be effective in laboratory or single-line settings tend to be unsuccessful when applied to various industrial settings.

It is a well-known problem in the wider computing community which is commonly tackled by domain adaptation, feature normalization, and transfer learning-standard techniques that are covered in the main AI and ML literature [10], [11], [12], [13], [14]. However, these methods are underutilized in the literature of injection molding. The majority of the published works are aimed at optimal predictive accuracy in a single dataset instead of deriving strong and transferable models [15], [16], [17]. Also, the differences in data preprocessing and feature engineering, as well as verification protocols, complicate the ability to compare the results of studies or are lacking best practices in model robustness [18], [19].

To fill this gap, this paper is a review of AI and ML applications that are already in use in injection molding in the lens of computational generalization and model transferability. The focus is not on assessing industrial performance, e.g., in terms of efficiency or quality gains, but rather on examining the manner in which existing and current body of knowledge addresses (or leaves unaddressed) the fundamental computing problems which will dictate whether an AI model can extrapolate outside of its training setting.

There are three contributions of the paper. First, it summarizes the literature in order to determine common technical shortcomings linked to data preprocessing, feature alignment, model regularization, and validation. Second, it presents a theoretical computing architecture that puts these components together to form a systematic journey to more generalizable AI in manufacturing. Third, it provides future opportunities such as benchmark datasets, lightweight adaptation strategies and reproducible cross-domain protocols which can be used in the next generation of AI-driven injection molding research [8], [20].

2. LITERATURE REVIEW

The recent adoption of artificial intelligence (AI) and machine learning (ML) into injection molding has changed significantly throughout the past twenty years, as the overall movement of manufacturing has shifted towards the paradigm of digital and data-driven manufacturing. The initial researchers mainly used AI to achieve higher-quality prediction and the optimization of processes in controlled conditions, whereas more recent publications focus on raising the adaptability, efficiency, and generalization of the system across machines, materials and the type of products of interest [2], [3], [4], [21], [9].

2.1 Early AI Applications and Foundational Methods

Early studies like Farooque et al. [2] highlighted how the quality of products is sensitive to the important process parameters, including the melt temperature, the mold temperature, and holding pressure. Classical optimization methods like Taguchi methods, response surface methodology (RSM), and genetic algorithms were popular with parameter tuning, but they could not be successfully generalized to a variety of different materials or part geometries [15], [16].

Shen et al. [15] used artificial neural networks (ANN) and genetic algorithms (GA) to ensure that the volumetric shrinkage was minimized, and therefore, successful mappings between the process parameters and the shrinkage variations were obtained, but their data set was restricted to one polymer grade and a single mold setup. On the same note, Altan [16] proved the efficiency of ANN based prediction of shrinkage in a controlled environment but admitted the lack of scalability to other machines.

The history of the early AI movement in manufacturing was similar to the work of swarm and hybrid optimization algorithms. Multi-hybridized swarm-intelligence and job-shop-scheduling optimization methods offered by Jebari et al. [22-26] could be used to see how multi-objective hybridization can be used to deal in trade-offs between cycle time, quality, and energy. These methods though not introduced in the context of molding have high potential regarding multi-criteria decision optimization in process-parameter control [27].

Such initial papers validated the predictive capabilities of AI and at the same time revealed its reliance on limited and domain-specific data [8], [10].

2.2 Advancements in Quality Prediction and Monitoring

With the development of sensor technologies and computational abilities, researchers started to combine real-time monitoring and quality prediction using AI. Park et al. [4] designed an AI-enhanced system which automatically manipulated process parameters based on temperature and pressure measurements measured in millions of molding cycles and minimized defects including warpage and shrinkage. Similar findings were made by Silva et al. [1] who used an integration of IoT, big-data, and ML models that led to improvements in OEE (12 per cent) and defect-detection accuracy (up to 98 per cent). However both experiments had to be configured individually to each machine resulting in no cross-domain scalability.

Mollaei et al. [21] used hybrid ML models to predict and eliminate blush defects in PVC bushings, with the GA optimization method reducing the area of defects by 81.7 per cent. Gim and Rhee [28] applied SHAP-based explainability to find the points on the process state where part quality was most correlated, enhancing interpretability but using single-mold data. Jung et al. [9] and Aminabadi et al. [29] suggested autoencoder-based and closed-loop AI systems, respectively, exhibiting high predictive accuracy but low cross-set-ups.

Other industries have been shown to have comparable AI structures. Jebari et al. [30] and [31] proposed smart multi-sensor and cloud-AI-based methods of precision agriculture and environmental surveillance, where the heterogeneity of data and real-time flexibility resembles the injection-molding quality control issues. These papers confirm the general design principles that can be transferred to combine distributed sensors, cloud analytics, and hybrid models [32].

2.3 Process Optimization and Adaptability

AI usage has extended past quality prediction because of the optimization literature. Zhao et al. [19] provided an overview of intelligent sensing and adaptive optimization, emphasizing the combination of reinforcement learning, surrogate modeling, and statistical analysis to perform parameter tuning in real-time. Ogorodnyk and Martinsen [18], highlighted how AI can decrease the time of the cycle and improve rapid heating/cooling systems but expressed the lack of standard frameworks to apply it on a larger scale.

When the source and target components have similar geometries, Lockner and Hopmann [17] have shown that transfer-learning can significantly decrease the amount of training-data needed to optimize ANNs, with great accuracy, to tackle the problem of model generalization directly in the injection molding process, this study was one of the few studies that pays explicit attention to model generalization. Gim et al. [33] further elaborated on this concept by the suggestion of an explainable AI-based optimization methodology that identified significant in-mold conditions, which provided more objective parameter modification, although still restricted to particular machines.

The future of injection molding is in hybrid optimization which is yet to be tested globally. Jebari et al. [22] optimized the use of nature-based optimization of scheduling through multi-objective hybridization and in another paper [23] incorporated swarm-intelligence concepts to achieve better convergence. By optimizing these techniques to process-parameter tuning, the local minima would be overcome and robustness increased in nonlinear molding systems [34].

2.4 Energy Efficiency and Smart Manufacturing

Along with studies of quality and optimization, AI has been also used to enhance sustainability and energy efficiency. The earliest models of energy monitoring and system level efficiency were defined by Thiede [35] and Dietmair and Verl [36]. Pascoschi et al. [37] also used a hybrid AI approach of combining autoencoders and clustering to optimize the use of energy by detecting the important variables that affect machine energy modes. The potential of ML-based energy monitoring was proven by Carvalho et al. [38] who identified the idle periods and allowed up to 30 percent energy savings per machine. Ghaleb et al.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[39] implemented the reinforcement learning in the dynamic scheduling, which showed enhanced production resilience and energy utilization.

The intersection of edge computing and AI in sustainable operations, like in the case of Jebari et al. [40] and [41] provides a new stimulus to injection molding. Their uber-AI IoT architectures decentralize intelligence across cloud and edge nodes, in order to minimize latency and computation. This may be achieved via the application of similar strategies to ensure near-real-time AI inference in molding plants coupled with systems of digital twin [42].

In spite of the fact that these studies point to the computing potential of AI in the context of sustainability, very few of them have really tested how trained models can be transferred between machines of different types, production lines, or factories- another aspect that indicates a lack of transferability [43], [44], [45].

2.5 Toward Interpretable and Scalable AI

Interpretability and transparency have become relevant as AI systems transform to industrial deployment. The LIME framework of explaining model outputs was proposed by Ribeiro et al. [46], which provides the basis of reliable AI in the manufacturing domain. Obregon et al. [47] reflect this explainability requirement, in injection molding, by jointly using rule-based explanations and ensemble models for sink-mark defect, obtaining accuracy and interpretability.

In the meantime, Zhang et al. [48] had shown a two-branch neural network of real-time detection of defects and the potential of vision based systems but noted that image annotation and intermold transferability were not perfect. Offering more of a review, Selvaraj et al. [49] reported that even though AI techniques, such as supervised, unsupervised, and reinforcement learning, could positively affect quality and productivity, their scalability and the cost of computation are the barriers to multi-domain application.

The usefulness of explainable hybrid systems that combine cloud intelligence and local edge analytics through which transparency, resilience, and adaptability of industrial AI could be enhanced is further highlighted by complementary research by Jebari et al. [30], [41].

2.6 Summary

Overall, the literature supports the high potential of AI to improve injection molding process in terms of efficiency, quality and sustainability. But almost all the reported models have one weakness; they all use single domain datasets with little tests on different operating conditions. The community does not have standardized preprocessing guidelines, benchmark data, and cross-machine validation techniques.

Even the most advanced systems, as explained by Silva et al. [1], Park et al. [4], and Lockner and Hopmann [17], have to be calibrated on a machine-specific basis, thus reducing the scale of deployment. All these repetitive shortcomings characterize the AI generalization gap in injection molding, where there is an urgent requirement of domain-sensitive preprocessing, standard validation, and explainable model design.

In general, the literature proves the high potential of AI to improve the efficiency, quality, and sustainability of injection-molding. Nonetheless, the weakness that is common in almost all of the reported models is the use of single-domain datasets with limited testing in different operating conditions [1], [37], [4], [21], [17], [33]. The community does not have standardized preprocessing guidelines, benchmark data, and cross-machine validation techniques.

Even the most developed systems need machine-specific calibration, as shown by Silva et al. [1], Park et al. [4], and Lockner and Hopmann [17], which restricts scalability to deployment. These systematic constraints characterize the AI generalization gap in injection molding- indicating that domain-sensitive preprocessing, standardized validation, and decipherable model design is required [8], [20].

Table 1 summarizes a sample of AI and ML research, both reflecting methodological advances and ongoing generalization problems. Nevertheless, an even greater set of algorithms, including shallow neural networks and genetic optimization [15], [16], [22], [23] and hybrid clustering [37] as well as transfer learning [17], use single-domain data and a small set of validation schemes. Even higher performing systems such as those of Silva et al. [1], and Park et al. [4] also demand per-machine calibration, whereas explainability-oriented works

[28], [33], [30], [41] deal with interpretability but do not concern cross-domain robustness. Taken together, these results prove that the model generalization is still the most vulnerable aspect of the present AI studies on injection molding [18], [19].

Table 1: Summary of Generalization limitations in AI and ML methods applied in injection molding

Study (Year)	Objective / Application	Algorithm / Method	Dataset Characteristics	Validation Strategy	Cross-Domain Evaluation	Reported Metric / Accuracy	Main Limitation on Generalization
Silva et al. (2023) [1]	Real-time quality prediction (OEE improvement)	ANN / SVM + IoT integration	Multi-sensor data from 3 machines, 2 products	Hold-out + per-machine retraining	✗	91–98 % accuracy (OEE +12 %)	Separate setup required per machine; long data-collection time limits scalability
Park et al. (2019) [4]	Autonomous quality control via pressure & temperature signals	ANN-based closed-loop control	Millions of cycles from one industrial line	Random split	✗	>95 % defect reduction	Validated on single machine; no cross-line testing
Mollaei et al. (2023) [21]	Blush-defect prediction in PVC bushings	ANN + GA optimization	Simulated + experimental single setup	10-fold CV	✗	99.99 % accuracy	Limited to PVC material and geometry
Gim & Rhee (2021) [28]	Interpretability of cavity-pressure profiles	NN + SHAP analysis	Single-cavity mold dataset	80/20 split	✗	R^2 = 0.93 (weight prediction)	Applicable only to similar pressure-curve shapes
Jung et al. (2021) [9]	Autoencoder-based quality prediction	Deep autoencoder	Single industrial dataset	Random split	✗	>95 % accuracy	Trained on one dataset; no multi-process validation
Lockner & Hopmann (2021) [17]	Transfer-learning for process optimization	ANN + fine-tuning approach	Data from similar geometries	Cross-geometry transfer	✓	≈ 90 % accuracy	Effective only for similar part designs
Pascoschi et al. (2024) [37]	Hybrid AI for energy optimization	Autoencoder + K-Means clustering	Shop-floor energy signals	k-fold CV	✗	Energy reduction ≈ 8 %	No validation across different machines

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Ogorodnyk & Martinsen (2018) [18]	AI for real-time process control	Survey / review of AI methods	Multiple case studies	Descriptive	✗	—	Lack of standardized framework and benchmarking
Zhang et al. (2022) [48]	Vision-based real-time defect detection	Two-branch CNN	Image dataset (single tool)	Train-test split	✗	>95 % defect detection accuracy	Limited camera resolution and annotation quality
Gim et al. (2024) [33]	Explainable AI for in-mold optimization	Hybrid ML + XAI	Real industrial dataset	k-fold CV	✗	>92 % accuracy	Validated on single machine only

3. IDENTIFIED COMPUTING CHALLENGES

3.1 Challenge 1 – Data Heterogeneity and Feature Standardization

The types of injection molding data range in structure, size and frequency of measurement. Melt temperature, holding pressure, and cooling time are taken differently between equipment and suppliers, which makes it difficult to transfer models between factories [1], [2], [4]. In the example, Silva et al. [1] indicated that their quality-prediction model needed different set-up and normalization processes on every machine. On the same note, Park et al. [4] and Jung et al. [9] utilized single-machine information with a fixed range of features, which could not be reused in different settings.

This heterogeneity demands standardized feature definitions and normalization methods, e.g. z-score or min-max scaling, so that comparisons can be made across datasets [10], [12]. The creation of universal schemas of features and metadata schemes would be useful in integrating with IoT-based monitoring systems and digital twins as well [42], [40]. The hybrid AI structures suggested by Jebari et al. [40] also help to support standardization efforts as it shows how single data schema can facilitate interoperability between distributed edge and cloud systems.

3.2 Challenge 2 – Model Overfitting and Lack of Domain Adaptation

The problem that is repeated in the literature reviewed is a high-accuracy inside the field where the models were trained and failure when applied to other areas. ANN-based defect prediction [21] and optimization [16] reported almost perfect accuracy although it was optimized to individual materials or geometries. Even the CNN-based vision systems [48] can only work well with fixed lighting system and camera configurations.

The most common learning methods in computing are regularization and transfer learning, as they address overfitting (i.e. L1/L2 penalties, dropout, cross-domain fine-tuning) [10], [13]. Lockner and Hopmann [17] have shown transfer learning can be used to decrease the amount of data required to maintain the same predictive accuracy. Nonetheless, a small amount of injection-molding research specifically measures domain adaptation. Future studies must consider cross-part or cross-machine validation to measure generalization, and take standardized benchmarks, akin to those in larger ML domains [10], [14].

3.3 Challenge 3 – Data Scarcity and Labeling Limitations

Injection molding yields mass amounts of process data, but labeled data sets that can be used in supervised learning are infrequent. A large number of experiments use simulated data (e.g., Moldflow) or small experimental batches, as is the case in Mollaei et al. [21] and Gim and Rhee [28]. This scarcity is increased by the high cost of defect annotation, privacy and inconsistent sensor configurations [29].

The latest developments in semi-supervised and unsupervised learning [10], [13] as well as autoencoders pretraining [9] and synthetic data generation may come to the rescue of the labeling burden. As an example, Jebari et al. [30] and [41] demonstrated that AI-IoT hybrid structures with real and synthetic sensor data enhance training in spatial systems. However, no systematic investigations of the effects of synthetic augmentation on generalization in the real world have been conducted yet [18].

3.4 Challenge 4 – Interpretability and Trust in AI Models

The deployment of AI in high-stakes manufacturing needs trust as a requirement. Before engineers change the machine parameters, they should figure out the reasons why a model makes certain predictions. SHAP and CAM are some techniques that have been used to visualize relevance of features in molding [50, 51, 28], which is reminiscent of interpretability frameworks like LIME proposed by Ribeiro et al. [46].

The technologies known as explainable AI (XAI) are essential to close the gap between computational inference and human reasoning [10], [14]. This can be supported by studies such as those of Jebari et al. [31] and [40] which illustrates interpretable hybrid AI structures that can improve transparency in real-time management. Although these have been made, interpretability tends to sacrifice performance, and not a lot of literature combines explainability with transferability. The creation of hybrid frameworks with high levels of both accuracy and interpretability is an important research objective in AI-assisted process control [48], [33].

3.5 Challenge 5 – Lack of Benchmarking and Standardized Evaluation

The majority of research papers compare models by their own procedures or small personal data, which makes it challenging to assess the performance of methods [37], [17]. Even bigger ones, like the work by Silva et al. [1] and by Pascoschi et al. [37] do not publish standardized benchmarks. This disintegration is an obstacle to reproduction and retards group movement.

The community would also make use of common repositories under reproducible ML standards, such as documentation of datasets, versioning, and cross-domain validation standards [14]. This type of infrastructure would coordinate injection-molding research efforts with other existing fields of AI that are based on shared benchmarks (e.g., ImageNet or UCI datasets) [10], [13]. Jebari et al. [41] also support the role of shared, multi-domain evaluation schemes to confirm model transferability between a heterogeneous system.

3.6 Challenge 6 – Integration and Computational Efficiency

The application of AI on a shop floor is limited by the needs of hardware, network, and time. Research works like Silva et al. [1] and Ogorodnyk & Martinsen [18] emphasize challenges in implementing complicated models in actual-time control loops. On the same note, sensor data in high frequency found in quality prediction [4], [9] have a tendency to overload the legacy systems, creating latency or resource bottlenecks.

The potential solutions include edge computing and model optimization [40], [41]. That can be bridged by lightweight architectures and compression mechanisms, e.g. pruning and quantization [10], [12]. By connecting with digital-twin platforms [42], it can allow a constant update of the virtual and real worlds to facilitate computational efficiency and adaptive learning of manufacturing conditions.

3.7 Summary

Overall, the assessed literature confirms the power of AI in changing the process of injection molding but reveals a general deficit between the laboratory and industry-wide implementation. To fill this gap, there is need to use systematic means of standardizing features, domain adaptation, interpretability, benchmarking, and deployment.

This part demonstrates the value of integrating the rigorous theory of computing with the practical constraints of the industrial-oriented AI, utilizing both theoretical considerations [10], [14] and applied considerations [30], [41]. Based on this synthesis, the primary contribution of this paper is a conceptual framework that integrates and structures established AI techniques—such as data normalization, transfer learning, and explainable AI (XAI)—into a dedicated, systematic pipeline for solving the generalization problem in injection molding. It is crucial to note that the novelty of this

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

work lies not in the invention of new algorithms, but in their purposeful integration and sequencing to address the specific, cross-domain challenges identified in the literature. This framework provides a structured roadmap to bridge the gap between isolated, high-accuracy models and scalable, trustworthy industrial AI systems. The following sections will detail this framework and propose a concrete plan for its future validation.

4. PROPOSED CONCEPTUAL FRAMEWORK FOR GENERALIZABLE AI IN INJECTION MOLDING

Reading through the reviewed studies, the promise of AI to revolutionize injection molding is confirmed but a persistent disparity between laboratory and industry-wide results is evident. To fill this gap, the researcher has to use systematic methods to standardize features, domain adaptation, interpretability, benchmarking and deployment.

This section brings together the understanding of theoretical computing [10], [14] and applied industrial AI [30], [41] by emphasizing the need to integrate rigor of algorithms and constraints of practice. A conceptual framework that summarizes these principles into a stepwise approach to the development of transferable and explainable AI systems in injection molding is provided next.

4.1 Step 1 – Data Acquisition and Preprocessing

Any generalizable AI model is based on accurate and consistent data acquisition. Time-series data that are usually measured by injection molding machines include temperature of the melt (Tm), temperature of the mold (Tmo), pressure (P), screw position (S), and cycle time (tc). Nonetheless, cross-machine compatibility is not frequently achievable as in the case of Silva et al. [1] and Park et al. [4] where standardized data structures are missing.

To address this, normalization ensures that all features are comparable and mitigates the influence of varying units or ranges:

$$x' = \frac{x - \mu_x}{\sigma_x}$$

where x' is the normalized feature, and μ, σ are the mean and standard deviation of that feature.

Alternatively, min–max scaling may be used:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}}$$

The standardization of features (e.g. pressure and temperature) keeps the later learning algorithms to work with balanced inputs, avoiding bias of scale-specific machine inputs [10], [12].

A new standard of AI-ready injection molding data may contain metadata descriptors, which may include sampling frequency, sensor type and calibration intervals- enabling interoperability between plants and manufacturers. Other well-structured strategies have been confirmed in distributed edge cloud settings [40], and this indicates high potential of standardisation of injection moulding data pipelines.

4.2 Step 2 – Feature Engineering and Selection

All process variables do not have the same contribution to part quality. Features that are redundant or correlated with each other carry a higher risk of overfitting and they add more complexity to the model. The statistical measure or regularization terms in the learning model can be used as feature selection guide [10], [13].

A common form of L2 regularization in the loss function is:

$$L = \frac{1}{N} + \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 + \lambda \|\omega\|^2)$$

where L is the total loss, λ the regularization coefficient, and ω the model weights.

Weights are limited by the penalty term and more stable and smoother models are achieved that can be adapted to unknown data [14].

Hybrid feature-selection techniques that utilize statistical relevance (e.g., ANOVA, correlation) with model-based measures of importance (e.g., SHAP values, feature weights) should receive priority in order to have greater generalization. Other similar principles of hybridization were shown in multi-sensor settings by Jebari et al. [30] and [41], who showed that statistical and AI-based relevance selection achieved better interpretability and performance.

4.3 Step 3 – Model Training and Domain Adaptation

After the feature set is identified, the model is trained with the help of appropriate ML algorithms.

Conventional approaches such as ANN or SVM are usually trained using single-domain data [21], [9]. Transfer learning can be used to facilitate domain adaptation [17].

In transfer learning, parameters from a source domain (Ds) are fine-tuned for a target domain (Dt):

$$\theta_t = \theta_s + \eta \nabla_{\theta_s} L_t(f_{\theta_s}(x_t), y_t)$$

where η is the learning rate, and Lt represents the loss in the target domain.

This adaptation approach, explored by Lockner & Hopmann [17], reduces the need for large retraining datasets when moving between similar part geometries or materials. The transfer learning could also be supported with reinforcement learning and adaptive scheduling that Ghaleb et al. [39] and Jebari et al. [22] explored, where models are capable of changing dynamically to different operating conditions.

Simultaneously, autoencoders may be used to solve the problem of data scarcity by training compressed representations:

$$L_{AE} = \|x - g(f(x)\|^2$$

where f and g denote encoder and decoder networks, respectively.

This technique enables semi-supervised learning in cases with limited labeled data and is foundational in modern deep learning workflows [13].

4.4 Step 4 – Interpretability and Model Evaluation

To be adopted by the industries, engineers need to have knowledge on how a model can arrive at the predictions. SHAP and CAM (Class Activation Mapping) are interpretability tools that give an insight into the reasoning behind the model.

The SHAP value for feature x_j quantifies its contribution to a specific prediction:

$$\phi_j = \sum_{S \subseteq F \setminus \{j\}} \frac{|S|!(|F|-|S|-1)!}{|F|!} \left[f_{S\cup\{j\}}(x_{S\cup\{j\}}) - f_S(x_S) \right]$$

where f is the predictive model and F is the set of all features.

This method allows improving the confidence of operators in decisions made by AI by emphasizing the most impactful variables (e.g., packing pressure or cooling time) [28], [46].

Evaluation metrics should go beyond accuracy alone to assess generalization:

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}, \quad \mathrm{MAE} = \frac{1}{N}\sum |y_i - \hat{y}_i|$$

To ensure transferability, cross-domain validation, in which models are evaluated on unknown machines or product geometrie. Jebari et al. [31], [40] highlighted the significance of explainable and adaptive validation in hybrid AI systems- a methodology that complies with the theme of explainability studies in molding [28], [33].

4.5 Step 5 – Deployment and Computational Efficiency

The implementation of AI on the production floor must take a trade off between accuracy and speed of computation. According to Ogorodnyk and Martinsen [18], heavy models have the potential of posing latency problems in real-time systems. Likewise, sensor data in high frequency used to predict quality [4], [9] may overwhelm the legacy systems creating a latency or tightness bottleneck.

Two strategies address this:

1. Model pruning, which removes low-importance weights:

$$W' = \{w_i \in W \| w_i \| > \tau\}$$

where τ is the pruning threshold.

2. Quantization, which converts 32-bit weights to lower precision (e.g., 8-bit), reducing memory and inference time [12].

By including these streamlined models into digital twins [42], it is possible to be able to synchronize simulated and real processes continuously. This architecture enables the self-learning schemes that can provide change in model parameters as new data get accessible.

4.6 Summary of the Framework

The proposed framework (Figure 1) consolidates the essential computing principles required for generalizable AI in injection molding:

- Standardization of data input,
- Regularization and feature relevance control,
- Cross-domain adaptation for transferability,
- Interpretability for operator trust, and

• Computational optimization for real-time deployment.

Formalization of these steps makes this research fill the gap between single applications of AI and scalable, explainable, and reproducible smart manufacturing systems. The framework is based on the theoretical AI concepts as well as the recent industrial innovations in the distributed hybrid systems, so it is positioned to become a key bridge between the fields of computing science and industrial implementation of AI.

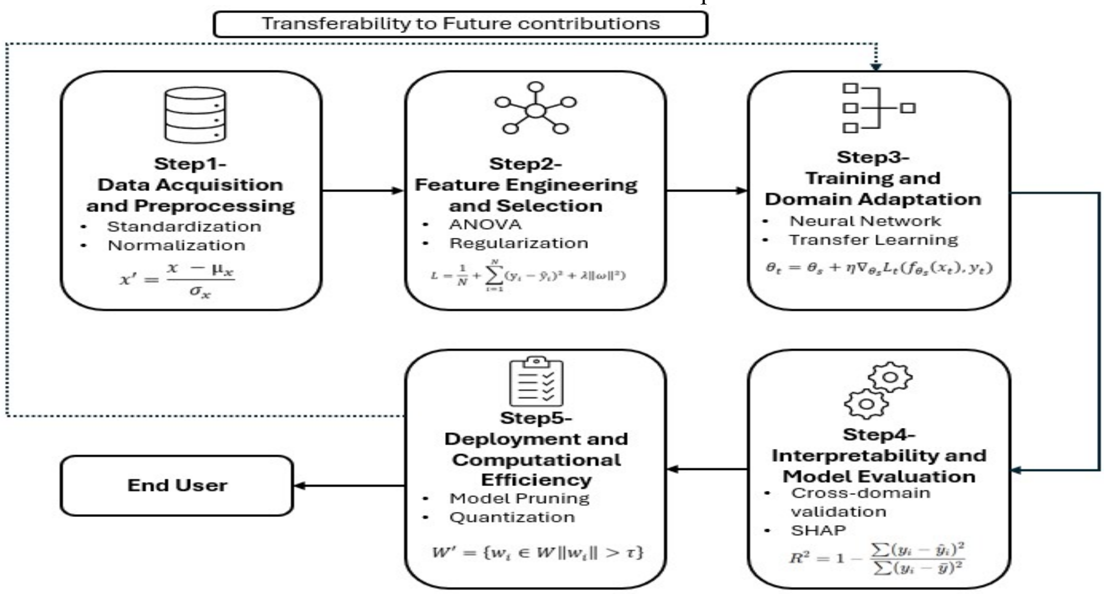

Figure 1: A conceptual diagram illustrating the five-layer framework from data acquisition to deployment, showing information flow and feedback loops between layers

5. DISCUSSION AND IMPLICATIONS

The suggested framework brings together both theoretical advances in computing and the practical requirements of the industry and presents a systematic way of building generalizable, interpretable, and efficient AI models in injection molding. Computer-wise, it helps solve the inherent problem of domain dependency that afflicts the majority of current models. In an industrial perspective, it will give practical advice on how to implement these computing principles in an actual production setting.

5.1 Comparative Analysis and Unintended Outcomes

When compared to prior studies, the proposed framework distinctively integrates generalization, explainability, and deployment efficiency into a single pipeline. While studies such as Silva et al. [1] and Park et al. [4] achieved high accuracy in single-machine setups, they required extensive retraining for new domains. In contrast, our framework leverages transfer learning and feature standardization to significantly reduce retraining effort. Similarly, while Lockner and Hopmann [17] demonstrated transfer learning for similar geometries, our approach extends adaptation to heterogeneous machines and materials through hybrid AI architectures.

However, the integration of multiple advanced techniques may introduce unintended complexities, such as increased computational overhead during the initial setup and a dependency on standardized metadata schemas that may not yet be widely adopted in industry. Furthermore, the reliance on synthetic data for benchmarking, while useful, may not fully capture real-world noise and variability, potentially leading to over-optimistic generalization estimates.

Table 2 compares the proposed framework with existing studies across key aspects such as generalization focus, explainability integration, and validation strategy.

Table 2: Comparison of the Proposed Framework with Existing AI Approaches in Injection Molding

Aspect	Prior Studies (e.g., Silva et al. [1], Park et al. [4], Lockner & Hopmann [17])	Proposed Framework	Significance of Difference
Generalization Focus	Limited to single machines/molds; minimal cross-domain validation.	Explicitly designed for cross-machine, cross-material generalization via domain adaptation and standardized preprocessing.	Enables scalable deployment without per-machine retraining, reducing time and cost.
Explainability Integration	Often omitted or treated as an add-on (e.g., SHAP applied post-hoc).	XAI (SHAP, CAM) embedded within the training and evaluation loop, ensuring interpretability from the outset.	Builds operator trust and facilitates regulatory compliance in high-stakes industries (e.g., medical, automotive).
Deployment Readiness	Rarely addressed; models often remain in experimental or cloud-based setups.	Incorporates edge computing, model pruning, and quantization for real-time, low-latency inference on shop floors.	Makes AI feasible for real-time control and integration with existing MES/PLM systems.
Validation Strategy	Typically uses single-dataset hold-out or k-fold CV without cross-domain testing.	Advocates for cross-domain validation, benchmark datasets, and phased real-world testing (pilot → multi-factory).	Ensures robustness and reproducibility, aligning with best practices in ML research.
Data Standardization	Ad-hoc preprocessing; lack of universal feature schemas.	Promotes standardized metadata schemas, normalization protocols, and IoT-ready data pipelines.	

5.2 Theoretical Implications

The framework in the computing field promotes the knowledge of generalizability of models in heterogeneous industrial systems. The suggested normalization and feature-standardization protocols formulate a common feature-space among machines, materials, and sensors - establishing the basis of domain adaptation methods, like transfer learning and fine-tuning [17], [10], [13].

Further structural feature selection and regularization of feature lists also lead to lower model variance and enhance reproducibility [14]. These concepts are consistent with hybrid optimization, like the example of Jebari et al. [22], which enhanced convergence and solution stability by hybridising swarm-intelligence, and Lockner and Hopmann [17], which minimised data demands in process optimization by transfer learning.

Besides, the explainable AI (XAI) systems, including SHAP and CAM, are integrated into the learning loop, which links the conventionally opaque nature of the deep learning models to the process parameters that are interpretable [28], [46]. This also helps towards what Ribeiro et al. [46] define as acceptable AI, wherein the transparency is vital towards realistic application in high-stakes industrial settings.

Incorporating the mathematical and computational ideas of normalization, regularization, loss minimization, and explainability into one workflow, the framework provides a contribution to the theoretical basis of domain-robust industrial AI. It also connects the older process systems engineering to new data-centric computing paradigms, promoting the

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

argument of more modular, hybrid, and explainable AI systems as observed in recent industrial computing research.

5.3 Industrial Implications

From an operational perspective, this framework can give manufacturers a roadmap on how to adopt AI in a more organized manner. Through normalization of data collection and model-transfer procedures, factories will be able to save time and cost of model retraining due to the introduction of a new machine, mould, or material [1], [4]. When sensor data are normalised and annotated using regular metadata schema then the predictive quality model developed on one machine can be fine-tuned, instead of having to be developed anew, on another [17].

Coupling to digital twins [42] allows learning in real-time data on production processes, enhancing the efficiency and responsiveness of processes to anomalies. This concept is similar to the edge cloud hybrid approaches described by Jebari et al. [40], which indicated that distributed AI can be low latency with synchronization to central digital systems.

Furthermore, pruning and quantization methods [12] are lightweight model deployment techniques that can easily be implemented on embedded controllers and edge devices, resulting in less latency and reliance on high-performance servers. These strategies are consistent with feasible limitations in the Industry 4.0 production area where the efficiency and reliability of computations are prime factors [18], [30].

Cross-functional collaboration is also encouraged by the framework. Data scientists are able to concentrate on the principles of modeling, whereas process engineers can be able to interpret AI outputs using the physically meaningful variables including melt pressure, mold temperature, and cooling time [2]. This common interpretability is essential to industrial adoption - particularly in highly-regulated industries, like automotive, electronics, and medical devices, where explainability and traceability are precursors to AI-based decision-making [20], [46].

5.4 Limitations and Future Directions

While the proposed framework offers a structured pathway toward generalizable AI in injection molding, several limitations must be acknowledged. First, the framework is currently conceptual and requires empirical validation through the multi-phase plan outlined in Section 5. Second, its effectiveness depends on the availability of standardized data schemas and metadata, which are not yet universally implemented in manufacturing environments. Third, edge-cloud hybrid architectures may introduce latency and synchronization challenges in real-time control loops. Finally, the framework assumes access to sufficient labeled or synthetically augmented data, which may be a barrier for small and medium-sized enterprises.

Future work will focus on:

- Empirical validation of the framework through industrial case studies and cross-factory trials.
- Development of open benchmark datasets for injection molding to foster reproducibility and comparative research.
- Integration of physics-based models with data-driven AI to enhance generalization under extreme or unseen conditions.
- Lightweight, federated learning strategies to address data privacy and scalability in multi-plant deployments.

5.5 Research and Implementation Outlook

Implementing the framework in practice will entail a multi-level approach.

On the research level, comparative evaluation of generalization techniques [10] will be possible by creating open benchmark datasets in injection molding, much like the case in computer vision. To encourage reproducibility, collaboration might be conducted in accordance with ISO [11] and IBM ML definitions [12] standards.

At the industrial level, the framework can be embedded into manufacturing execution systems (MES) and product lifecycle management (PLM) systems to enable standardisation of AI processes between facilities, just as the AI-readiness principle suggested to SMEs has (Bettoni and Matteri [20]).

The framework needs to be tested in cross-domain conditions, that is, training models in one plant and implementing them in another facility, to determine the performance of a transfer when there are material, geometry and machine brand differences [17]. Even more robust physics-AI methods that employ simulation together with data-driven inference would be more effective [42], [13].

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Overall, this curriculum is an evolution in computing, through codifying princcipled domain-generalization, as well as a realistic plan for industrial implementation, through specifying the infrastructural, computational, and methodological processes involved in the widespread adoption of AI. It will turn AI in injection molding into a niche-focused research field that can be scaled, interpreted, and reproduced as an extension of the wider view of intelligent manufacturing systems.

5.6 Research and Implementation Outlook

While this paper introduces a conceptual framework, its practical efficacy must be empirically validated. To this end, we propose a multi-stage validation plan to test the hypotheses embedded within the framework and transition it from a theoretical model to a proven methodology.

1. Phase 1: Benchmarking on Public and Synthetic Data: The first phase will involve the creation of a benchmark dataset. This can be achieved by:

   - Curating Public Data: Aggregating publicly available injection molding data from various sources, ensuring it encompasses different machines, materials (e.g., ABS, Polypropylene), and part geometries.

   - Generating Synthetic Data: Using high-fidelity simulation software (e.g., Moldflow) to generate data for a range of process conditions and defect scenarios, explicitly introducing domain shifts by varying machine parameters and material models.

     The framework will be applied to this benchmark, and its performance will be compared against baseline models trained without its prescribed steps (e.g., without domain adaptation or feature standardization). Key metrics will include cross-domain accuracy, F1 score, and mean absolute error when models are trained on one domain and tested on another.

2. Phase 2: Case Study Application & Retrospective Analysis: We will conduct a detailed case study applying the framework to a real-world, multi-machine production environment. This will involve collaborating with an industrial partner to collect data from multiple injection molding machines producing similar parts. We will rigorously follow the five-step framework:

   - Step 1-2: Apply standardized data acquisition and feature selection across all machines.

   - Step 3: Train a model on a "source" machine and use transfer learning to adapt it to a "target" machine.

   - Step 4: Employ XAI techniques like SHAP to interpret the model's predictions on both machines, verifying that the reasoning aligns with physical principles.

   - Step 5: Deploy a pruned and quantized version of the model on an edge device for real-time inference.

     The success criteria will be a significant reduction in the required retraining data and time for the target machine while maintaining high predictive accuracy and gaining operator trust through explainability.

3. Phase 3: Cross-Factory Validation: The ultimate test of the framework's generalizability will be its application across different factories with distinct machine brands, sensor types, and environmental conditions. This phase will assess the framework's ability to facilitate model transfer in the most challenging, heterogeneous environments.

This structured validation plan will provide the empirical evidence necessary to confirm the framework's utility and refine its components, ultimately paving the way for its adoption as a best-practice guideline in AI-driven injection molding.

This diagram (Figure 2) visually summarizes the proposed validation plan, making it easy to grasp the progression from concept to real-world proof.

Journal of Theoretical and Applied Information Technology
31st January 2026. Vol.104. No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

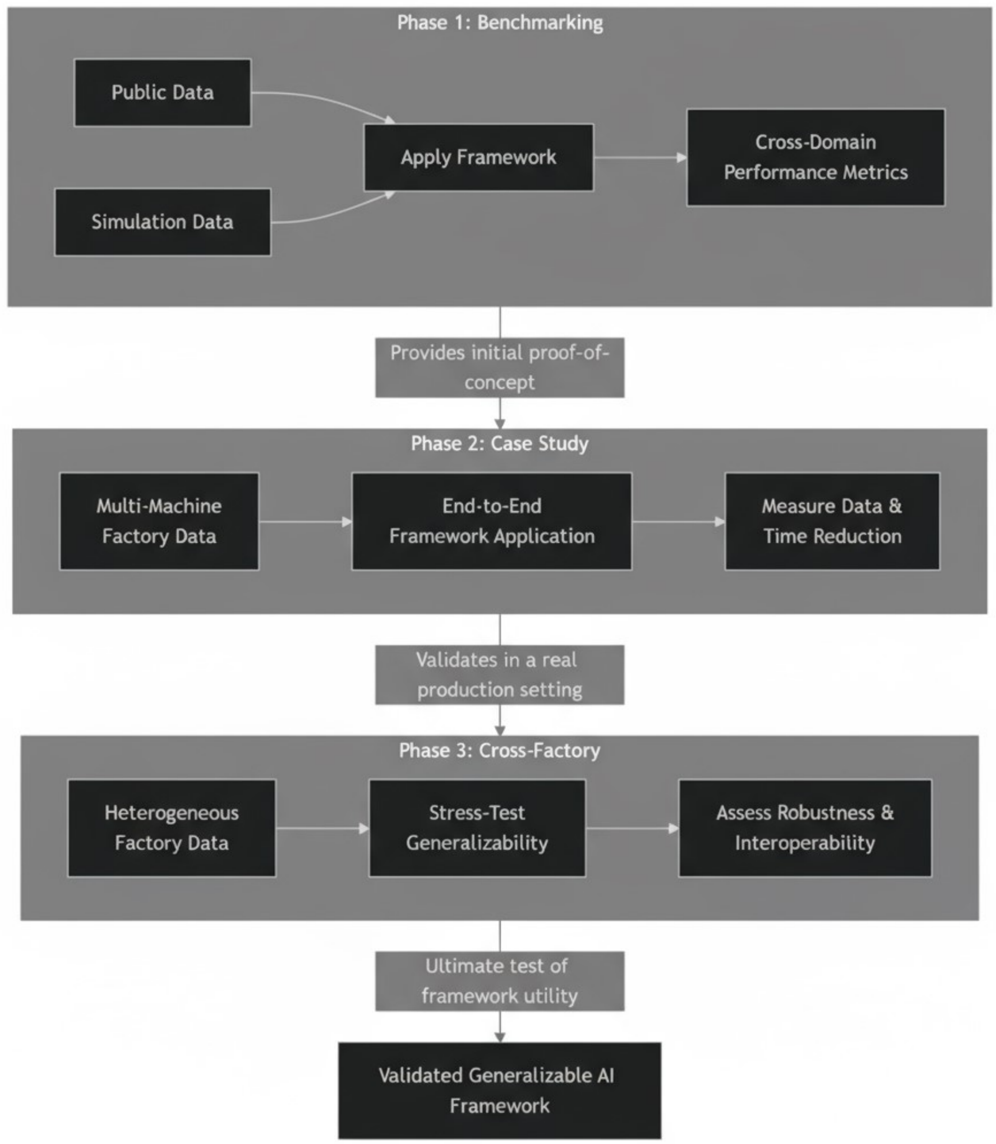

Figure 2: The multi-phase validation plan for the proposed framework, progressing from controlled benchmarks to real-world industrial deployment

6. CONCLUSION

This paper has introduced a computationally-structured framework designed to address the generalization gap in AI applications for injection molding. Through a systematic review of the literature, we identified key challenges—data heterogeneity, model overfitting, lack of explainability, and deployment inefficiencies—that limit the scalability of existing AI solutions. The proposed 5-step framework integrates data standardization, feature selection, transfer learning, explainable AI, and edge-aware deployment into a cohesive pipeline aimed at achieving cross-domain robustness and operational trust.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

While the framework is conceptual, it provides a clear and actionable roadmap for researchers and practitioners to develop scalable, interpretable, and efficient AI systems. Its novelty lies not in the invention of new algorithms, but in their purposeful integration and sequencing to tackle the specific cross-domain challenges prevalent in injection molding. Future work will focus on empirical validation through benchmarking, industrial pilot studies, and cross-factory implementations, ultimately paving the way for the widespread adoption of generalizable AI in smart manufacturing ecosystems aligned with Industry 5.0 visions.

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