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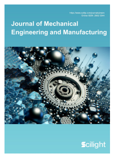

Review

Minds and Molds: What Can Artificial Intelligence Do for Multi-Material Injection Molding

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Abstract: Multimaterial injection molding (MMIM) enables the integration of distinct polymer properties within a single component, but its tightly coupled thermal–rheological dynamics and interfacial phenomena complicate process control and quality assurance. Concurrently, advances in artificial intelligence (AI) and machine learning (ML) are reshaping manufacturing through predictive modeling, adaptive optimization and data-driven control. This review critically synthesises AI/ML methods and adjacent optimisation and control frameworks relevant to MMIM, distinguishing learning-based predictive models from conventional statistical, surrogate-based, and simulation-assisted approaches. Within this framework, methods such as artificial neural networks, radial basis function models, genetic algorithms, hybrid intelligent optimisation, and sensor-integrated control strategies are mapped against key manufacturing challenges including weld lines, sink marks, short shots, warpage, burn marks, and flow marks. Evidence from 2010–2025 shows that AI can improve dimensional stability, defect prediction and parameter selection, reduce experimental trial-and-error, and support intelligent monitoring. The most promising direction is the integration of AI with in-mold sensing, simulation and closed-loop control for real-time compensation. However, broader adoption requires high-quality datasets, standardized benchmarks, robust cross-material generalization and interpretable models validated in factory conditions. We outline a research agenda to bridge laboratory demonstrations and scalable industrial implementation, positioning AI as an enabler of more robust, adaptive and sustainable MMIM.

Keywords: machine learning; multi-component molding; defect prediction; in-mold sensing; predictive process control; intelligent manufacturing

1. Introduction

Injection molding (IM) is one of the most widely used polymer-processing technologies owing to its productivity, dimensional precision, and suitability for high-volume manufacture of complex components [1]. Its broad industrial adoption is attributable to a distinctive combination of advantages, including high production efficiency, excellent dimensional precision, relatively short cycle times, and the capacity to produce geometrically complex components with tight tolerances [2]. In multimaterial injection molding (MMIM), however, the process becomes substantially more complex because material compatibility, interfacial behaviour, sequence-dependent filling, and differential cooling must be controlled simultaneously. It is this added complexity that makes MMIM a particularly relevant domain for data-driven modelling, intelligent monitoring, and AI-assisted optimisation [3]. As shown schematically in Figure 1, these four stages collectively govern the mechanical performance, surface quality, and dimensional accuracy of the molded part.

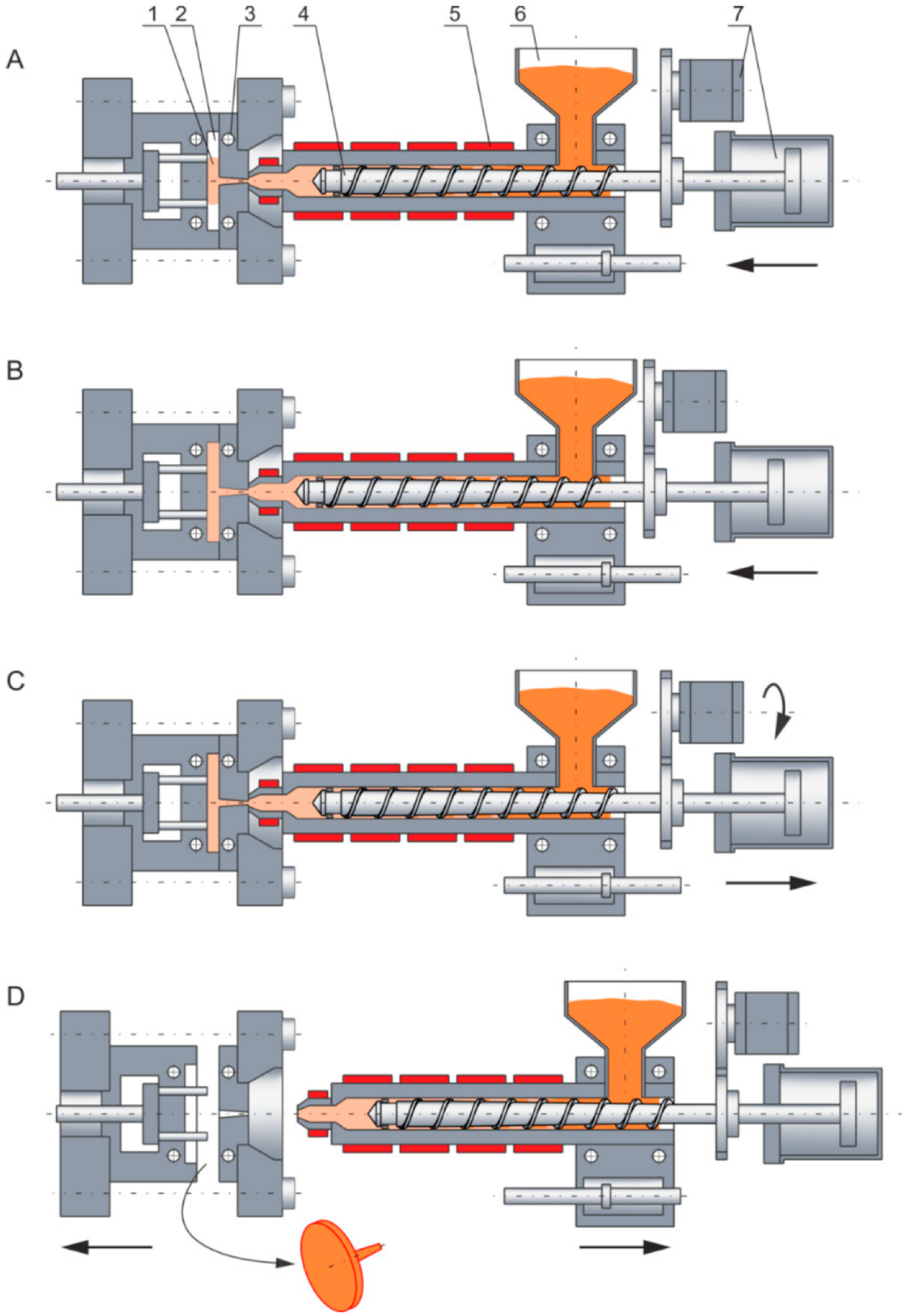


Figure 1. Injection molding cycle: (**A**) injection/filling, (**B**) holding/packing, (**C**) plasticisation/melting, and (**D**) mold opening and part ejection; 1—molded part, 2—mold cavity, 3—cooling channels, 4—screw, 5—heaters, 6—hopper, 7—drive system.

Although IM is a mature and well-established manufacturing technology, its efficiency and product quality remain highly sensitive to the selection and control of process parameters. Variables such as melt temperature, mold temperature, injection pressure, injection speed, cooling time, and packing pressure exert a major influence on the final characteristics of the product. Inappropriate parameter combinations may lead to defects such as weld lines, sink marks, voids, warpage, incomplete filling, and surface imperfections. For this reason, extensive research has been devoted to process optimisation through statistical design-of-experiments methods, response-surface modelling, and simulation-assisted analysis. In particular, Taguchi-based robust-design approaches have proved effective in identifying influential factors, improving dimensional stability, reducing defect formation, and minimising process variability under controlled experimental conditions. Likewise, simulation-assisted and metamodel-based optimisation have been used to define processing windows and improve responses such as shrinkage, warpage, filling behaviour, and surface quality [4].

In recent years, however, the growing complexity of polymer products and manufacturing requirements has revealed the practical limits of purely offline optimisation strategies when applied to highly coupled manufacturing systems. This is particularly relevant in multimaterial injection molding (MMIM), where thermo-rheological behaviour, interfacial adhesion, material compatibility, and machine-dependent variability generate nonlinear interactions that are not always captured efficiently by conventional design-of-experiments or single-response simulation studies. Accordingly, artificial intelligence (AI), machine learning (ML), and other data-driven methodologies should be understood not as replacements for Taguchi or other established optimisation methods, but as complementary tools capable of extending process optimisation towards multivariate prediction, adaptive parameter adjustment, and real-time process control [5,6]. Such techniques can analyze large process datasets, identify nonlinear interactions among variables, and predict manufacturing outcomes with greater sophistication than many conventional methods.

The application of AI in injection molding has therefore attracted increasing attention in both academic and industrial contexts. AI-based systems can support a variety of manufacturing functions, including real-time process monitoring, adaptive control of injection parameters, predictive maintenance of equipment, optimization of mold design, and intelligent cooling-channel configuration [7]. The IM procedure comprises three interlinked process loops (see Figure 2). The initial loop, known as machine control, involves regulating machine parameters such as speed, pressure, and temperature. The middle loop, termed process control, encompasses variables like in-mold temperature and pressure. The final loop, identified as set point control, manages feedback related to part quality [8,9].

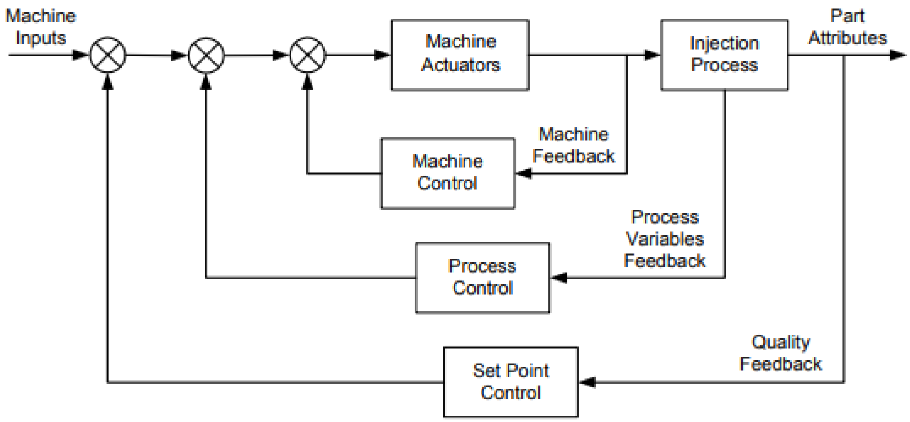


Figure 2. Block diagram of three IM control loops.

By analyzing sensor data and machine signals, these systems can detect deviations from optimal operating conditions and recommend, or even implement, corrective adjustments during production. Likewise, data-driven optimization can reduce the need for extensive experimental trials by identifying favourable processing windows for complex material systems and component geometries [7].

Fu et al. [10] developed a novel concurrent optimization algorithm to simultaneously optimize the structural geometry and injection gate locations. The full sensitivity of the concurrent optimization problem was derived and the sensitivity of multimaterial distribution against injection gate locations was calculated with a finite difference-based method. The numerical results prove that the overall structural compliance can always be further reduced with the concurrent optimization scheme. Muaz et al. [11] developed a novel approach to improve the prediction of product quality characteristics in plastic injection molded parts. A Multitask Encoder–Decoder Model was developed, which is capable to establish a linkage between process parameters of IM machines (e.g., IM pressure) and multiple output quality characteristics of the finished part (e.g., weight). Moayyedian and Mamedov [12] developed a quality-evaluation framework that combined the Taguchi method, the fuzzy analytic hierarchy process, and the technique for order preference by similarity to the ideal solution (TOPSIS, Figure 3) in order to determine the process-parameter configuration associated with the highest moldability manufacturing index and reduced defect formation. Their results demonstrate that Taguchi-based design remains a practical and experimentally efficient foundation for robust parameter selection, particularly when integrated with multi-criteria decision-support tools. This example illustrates that conventional optimisation methods remain highly valuable for factor screening and variability reduction, even though more advanced AI-based approaches may offer additional advantages when the process space becomes strongly nonlinear, data-rich, or dynamically variable. Farahani et al. [13] introduced an Industry 4.0 framework to effectively predict and manage maintenance operations in plastic IM plants using both edge and cloud computing opportunities. The focus of the framework was on creating connected systems and integrating data from multiple sources to detect any signs of maintenance issues (see Figure 4). Kumar et al. [14] studied a data-driven cyber-engineering control framework in which cavity temperature and pressure thresholds, coupled with an if–then rule-based algorithm, enabled compensatory process adjustments, thereby reducing quality-failure rates and resource wastage in IM.

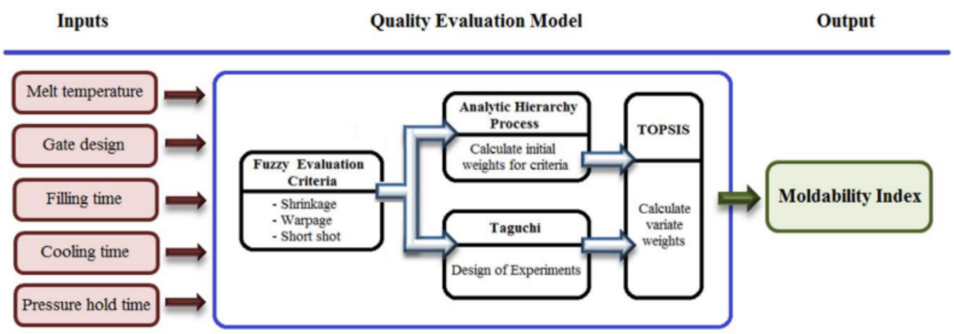


Figure 3. The schematic representation of multi-objective optimization process [12].

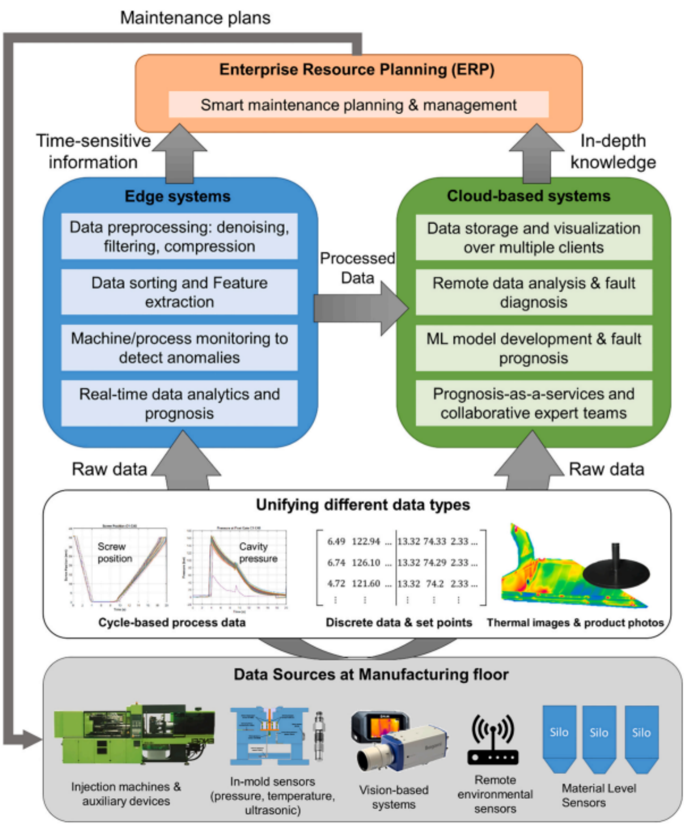


Figure 4. Architecture of a predictive maintenance framework [13].

Machine-learning approaches build directly upon empirical and statistical information derived from the manufacturing process [15]. In the context of injection molding, such models are typically trained on datasets obtained from designed experiments, historical production records, in-mold sensor measurements, qualityinspection data, and, in some cases, simulation-generated outputs [16]. Statistical methods remain fundamental throughout this workflow, including in experimental design, variable selection, parameter estimation, uncertainty assessment, and model validation. The distinctive contribution of AI therefore lies not in replacing empirical evidence, but in learning complex, nonlinear, and multivariate relationships from such data in order to support prediction, optimisation, and adaptive process control. Consequently, the availability of high-quality datasets is a prerequisite for reliable AI deployment, since model accuracy and generalisability depend strongly on data representativeness, measurement fidelity, and adequate coverage of the relevant processing domain [17].

Pinto et al. [18] developed a MATLAB® algorithm to determine the optimal Reynolds number for a given flow rate and velocity, thereby providing the gating geometry in a die casting process. The specific value of the objective function remains unknown until simulation outcomes are acquired [17]. To address the optimization problem, two methods are employed: direct optimization and metamodel-based optimization, as illustrated in Figure 5.

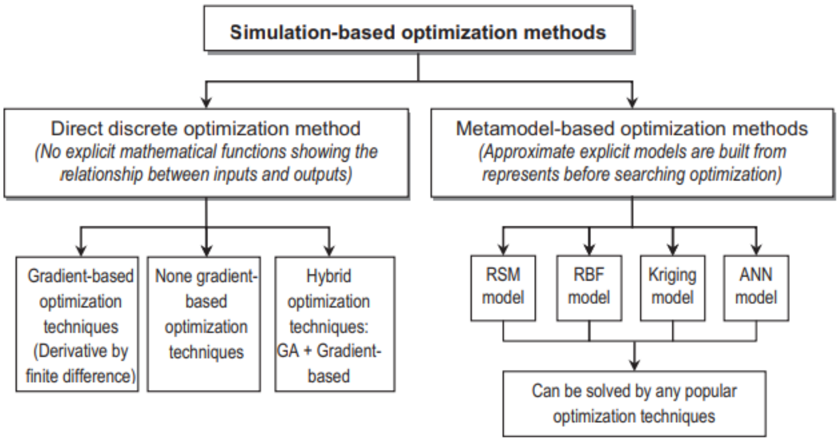


Figure 5. Classification of optimization methods [17].

These developments are particularly relevant to MMIM, in which two or more materials are combined within a single component in order to integrate distinct functional properties [19]. MMIM offers clear advantages [20] in multifunctional design, lightweight construction, and material efficiency, but it also introduces substantial technical challenges associated with interfacial adhesion, rheological mismatch, sequence-dependent flow behaviour, and differential cooling. These coupled effects make process design and optimisation more demanding than in conventional single-material molding and help explain why AI-assisted modelling, sensing, and control are of growing interest in this field [21].

A further challenge lies in the limited availability of systematic scientific investigations into multimaterial process optimization and modeling. Much of the practical knowledge in this field has historically been derived from empirical industrial practice rather than from comprehensive analytical and experimental research. As a result, there remains a significant need for structured studies capable of improving understanding of multimaterial flow behavior, interfacial bonding mechanisms, and robust optimization strategies [22].

In this context, the increasing availability of digital manufacturing tools, advanced sensing systems, data analytics, and machine learning provides a promising route to address these limitations. By integrating AI with real-time monitoring, process simulation, and sensor-based control, it becomes possible to develop intelligent manufacturing frameworks capable of optimising MMIM processes dynamically. Such approaches have the potential to improve process stability, reduce defect formation, enhance reproducibility, and accelerate the industrial implementation of next-generation multimaterial products.

Accordingly, the present study examines the emerging role of artificial intelligence and data-driven methodologies in MMIM. It aims to provide a systematic and critically informed overview of how AI-based tools may contribute to improved process optimization, enhanced reliability, and broader industrial adoption of intelligent MMIM technologies.

The scientific contribution of the present review lies not in the proposal of a new algorithmic method, but in the systematic consolidation and critical interpretation of a fragmented research field situated at the intersection of multimaterial polymer processing, intelligent manufacturing, and data-driven optimisation. The novelty of the article resides in four principal aspects. First, it brings together evidence on AI applications specifically relevant to MMIM, a domain in which the literature remains comparatively dispersed and often embedded within broader studies on conventional injection molding. Second, it analyses AI not only as a predictive tool, but as part of a wider manufacturing architecture involving sensing, simulation, defect mitigation, and closed-loop process control. Third, it compares technological promise against practical implementation constraints, including data quality, model transferability, interpretability, and industrial validation. Fourth, it develops a forward-looking synthesis that identifies the principal research gaps that must be addressed before AI-assisted MMIM can progress from laboratory demonstration to robust factory-scale deployment.

The manuscript is organised Section 1 which establishes the contextual and theoretical foundations by introducing IM as a key manufacturing process and by outlining the increasing importance of multimaterial processing and AI-assisted manufacturing. Section 2 defines the conceptual scope and scholarly contribution of the work, with particular emphasis on the integration of artificial intelligence into MMIM and on the potential of data-driven control and modeling to improve process performance. Section 3 describes the research methodology, including the information sources, literature-selection strategy, and analytical framework adopted to ensure transparency, reproducibility, and methodological reliability. Section 4 presents the organisational structure of the paper and clarifies how the thematic sections collectively address the study’s core objectives.

Section 5 offers a critical synthesis of the existing literature, covering multimaterial processing technologies, interfacial behavior, process-parameter optimization, mold design, and the application of AI to monitoring, modeling, and predictive control. Section 6 develops an integrative discussion of converging and diverging research trends, major technological barriers, and the likely role of AI in shaping the future development of MMIM. Finally, Section 7 summarises the principal contributions of the study, outlines implications for research and industrial practice, and identifies promising directions for future work.

In the interest of scholarly transparency, the study also acknowledges its limitations, particularly those associated with the availability of published data, methodological diversity across the literature, and the rapidly evolving nature of AI applications in polymer manufacturing. Nevertheless, the paper aims to offer a coherent and rigorous perspective on how intelligent, data-driven methodologies may support the advancement of MMIM and contribute to broader innovation within the injection molding sector.

Although selected studies on conventional IM are discussed in the present review, they are included only where they provide transferable mechanistic, methodological, or modelling insights relevant to MMIM. The principal analytical focus of the article remains on phenomena that are either specific to, or substantially intensified by, multimaterial processing, including interfacial adhesion, material compatibility, sequencing effects, differential thermal histories, coupled flow behaviour, and defect formation at multimaterial interfaces. Accordingly, general injection-molding literature is treated here as contextual background rather than as the primary object of review.

2. Method of Research

A structured and comprehensive literature review was conducted using a transparent and reproducible research methodology. The review procedure was designed in accordance with the PRISMA 2020 guidelines [23,24], thereby ensuring methodological consistency, procedural transparency, and replicability throughout the study [25]. The identification and evaluation of relevant sources were guided by recognised scholarly quality indicators, including citation influence and the academic credibility of the publication outlets.

Data collection was performed in January 2026, with the initial set of bibliographic records primarily obtained from the CrossRef database, selected for its extensive indexing coverage across engineering and manufacturing research domains. To broaden the scope of the search and improve the completeness of metadata retrieval, additional indexing platforms, particularly Dimensions.ai, were also consulted.

To facilitate the systematic consolidation of records obtained from multiple databases, a customised MATLAB® routine was developed. This tool enabled the automated integration of search outputs [26], standardisation of bibliographic metadata, and the identification and removal of duplicate entries. The adoption of this semi-automated workflow contributed to improving both the efficiency and reliability of the literature selection process.

2.1. Search Strategy and Information Sources

Building upon the PRISMA-based methodological framework outlined above, the literature search strategy was specifically designed to capture studies addressing the application of Artificial Intelligence (AI) and Machine Learning (ML) in MMIM, rather than general investigations of polymer processing or conventional injection molding optimisation. Thematic precision and retrieval relevance were ensured by structuring the search protocol around three complementary conceptual groups of search terms.

The first group addressed injection-molding technologies, including terms such as "injection molding", "multimaterial injection molding", "multi-component molding", "two-shot molding", "2K molding", "co-injection molding", "sandwich molding", and "overmolding". The second group encompassed artificial-intelligence and data-driven modelling approaches, incorporating terms such as "artificial intelligence", "machine learning", "neural networks", "deep learning", "genetic algorithms", "data-driven modelling", and "predictive analytics". The third group addressed process-optimisation and quality-related aspects, including "process optimisation", "defect prediction", "process control", "quality prediction", "parameter optimisation", and "intelligent manufacturing".

The Boolean search logic followed the general structure:

("Injection Molding" OR "Multimaterial Injection Molding" OR "2K Molding" OR "Co-injection") AND ("Artificial Intelligence" OR "Machine Learning" OR "Neural Network" OR "Data-driven Modeling") AND ("Process Optimization" OR "Defect Prediction" OR "Quality Control" OR "Predictive Control")

Search queries were applied to the title, abstract, and keyword fields of the selected databases. To ensure the scientific relevance and comparability of the collected literature, several eligibility criteria were implemented. These included:

- Publication period: 2010–2025
- Document type: peer-reviewed journal articles and review papers
- Language: English

These database search terms were used exclusively for literature retrieval and should not be conflated with the manuscript's indexing keywords provided beneath the abstract. These criteria were introduced to ensure that the review captured the most relevant contemporary developments in AI-driven optimization and intelligent control of IM processes, while excluding publications outside the scope of polymer processing, data-driven manufacturing, or multimaterial molding technologies.

Although the conceptual search logic was shared across databases, minor adaptations to syntax, indexing structure, and field-tag conventions were required in order to maintain semantic equivalence across CrossRef.

2.2. Study Selection and Screening

The identification and selection of relevant studies followed the PRISMA 2020 guidelines, ensuring methodological transparency, traceability, and reproducibility throughout the review process. The initial bibliographic search was conducted across the Web of Science, Scopus, and CrossRef databases and returned a total of 343,112 records covering the period 2010–2025. The substantial volume of initial results largely reflects the extensive indexing scope of CrossRef and associated metadata repositories, which frequently include duplicate records originating from publisher-level indexing, early-access publications, and cross-database overlaps.

To address these redundancies, an automated consolidation procedure was implemented using a bespoke MATLAB® script, complemented by manual verification. This process harmonised bibliographic metadata across the different sources and systematically eliminated duplicate entries. Following the combined automated and manual deduplication stages, 12,805 unique records were retained for preliminary screening.

Subsequently, screening and eligibility decisions were conducted in accordance with predefined inclusion and exclusion criteria, which had been established prior to database querying in order to minimise subjective bias and ensure methodological consistency. Titles, abstracts, and keywords were examined to evaluate their relevance to MMIM and the application of artificial intelligence or data-driven modeling approaches within polymer processing and intelligent manufacturing environments. Particular attention was given to studies addressing process optimization, defect prediction, process monitoring, material compatibility, and the functional performance of multimaterial molded components.

Publications lacking methodological transparency, those not addressing IM processes, or studies unrelated to multimaterial systems or AI-based modeling approaches were excluded during this stage. Following this screening procedure, 9614 studies were retained for full-text evaluation. A significant proportion of excluded publications addressed conventional IM or polymer processing without incorporating multimaterial configurations or data-driven analytical methodologies.

The final stage involved a detailed full-text assessment of the remaining studies to determine their methodological robustness, industrial relevance, and conceptual coherence with the objectives of this review. After the application of the established eligibility criteria, a final corpus of 184 peer-reviewed publications was retained. As a limited number of journals accounted for a disproportionately high share of the retrieved contributions, citation impact and scientific relevance were considered to mitigate potential publication-source bias. The resulting dataset therefore represents a curated body of literature comprising the most influential and methodologically robust studies addressing artificial intelligence, process optimization, and intelligent control strategies in IM systems, with relevance to multimaterial processing environments.

During the review process, a recurring challenge concerned the lack of standardised terminology within the IM and polymer processing literature. Identical processes are frequently described using different terminology, such as two-shot molding, 2K molding, bi-injection, co-injection, or multi-component molding. Similarly, variations occur in the naming of optimization and modeling approaches, where terms such as machine learning, data-driven modeling, and artificial intelligence are occasionally used interchangeably despite methodological differences. These inconsistencies required careful cross-verification of process descriptions, material systems, and modeling approaches during the classification of the retrieved studies. In addition, minor variations in terminology arising from differences between American and British English (for example mold versus mold) introduced further inconsistencies within bibliographic records.

The formulation of precise Research Questions (RQs) constitutes a fundamental element of any systematic literature review, as it defines the analytical scope and conceptual direction of the investigation. To ensure internal coherence and alignment with contemporary developments in intelligent manufacturing and polymer processing, the Population–Intervention–Comparison–Outcome–Context (PICOC) framework was adapted for the present study as follows:

- Population: Experimental, numerical, and review studies addressing the design, optimization, monitoring, or control of IM processes, with particular emphasis on multimaterial or multi-component molding systems used to produce polymer components with integrated functional properties.
- Intervention: Artificial-intelligence and machine-learning approaches relevant to IM and MMIM, together with adjacent data-driven, surrogate-based, and optimisation frameworks used as comparators or enabling methods. These include learning-based predictive models such as artificial neural networks and related machine-learning algorithms, evolutionary and computational-intelligence methods such as genetic algorithms and fuzzy systems, and hybrid frameworks that combine AI/ML with simulation, statistical modelling, or process-control strategies.
- Comparison: Comparative analyses between conventional statistical optimization techniques and AI-based modeling approaches, as well as comparisons between single-material and multimaterial molding strategies with respect to process performance, defect occurrence, and manufacturing efficiency.
- Outcomes: Improvements in process parameter optimization, defect prediction accuracy, dimensional stability, material compatibility, production efficiency, and overall process reliability, alongside the identification of emerging technological trends and unresolved research challenges within intelligent IM systems.
- Context: Peer-reviewed academic and industrial publications addressing IM technologies, multimaterial processing strategies, artificial intelligence applications, and intelligent manufacturing systems, published between 2010 and 2025.

Based on this framework, a structured and hierarchically organised set of Research Questions was established to guide the systematic extraction, critical evaluation, and synthesis of the knowledge contained within the selected literature. These research questions are presented in Table 1 of the manuscript.

The present review considered peer-reviewed publications published between 2010 and 2025, with particular emphasis placed on the most recent decade of research addressing the application of artificial intelligence and data-driven modeling techniques within IM processes, especially in the context of multimaterial and multi-component molding technologies. This timeframe was selected to capture the rapid technological developments associated with intelligent manufacturing, machine learning applications, and digital process optimization in polymer processing. For the purposes of the present review, optimisation is not interpreted through a single universal objective function, but rather through a multi-criteria performance framework reflecting the diversity of MMIM applications reported in the literature. Accordingly, comparative synthesis considers three principal groups of quantitative criteria. The first comprises defect-related criteria, including warpage magnitude, sink-mark depth, short-shot occurrence or filling deficiency, weld-line severity or strength reduction, and interfacial delamination. The second comprises dimensional and mechanical criteria, including shrinkage, dimensional deviation, part-weight consistency, interfacial bond strength, and the mechanical performance of the molded component. The third comprises process-efficiency criteria, including cycle time, process variability, scrap rate, and, where reported, material or energy consumption. Within this framework, an optimisation strategy is considered favourable when it improves one or more of these response variables without introducing unacceptable deterioration in the others.

Table 1. PICOC RQ's.

ID	Research Question
RQ1	What are the principal process-related challenges and defect mechanisms affecting the quality, reliability, and functional performance of components produced through MMIM?
RQ1.1	How do defect formation mechanisms—such as weld lines, sink marks, short shots, warpage, and interfacial delamination—manifest in MMIM compared with conventional single-material molding processes?
RQ1.2	Which material properties and processing variables (e.g., melt temperature, injection pressure, cooling rate, and material compatibility) most strongly influence interfacial integrity and mechanical performance in multimaterial molded components?
RQ2	How can Artificial Intelligence and Machine Learning techniques be applied to enhance process optimization, monitoring, and control in MMIM systems?
RQ2.1	Which AI-based modeling approaches—such as artificial neural networks, genetic algorithms, fuzzy logic systems, and hybrid optimization frameworks—have demonstrated the greatest effectiveness in predicting part quality and optimising process parameters?
RQ2.2	To what extent can AI-driven models improve the prediction and mitigation of common IM defects through data-driven process control strategies?
RQ3	How do process parameters, machine configurations, and mold design characteristics influence the stability and reproducibility of MMIM operations?
RQ3.1	Which process variables (e.g., injection speed, holding pressure, melt temperature, mold temperature, and cooling conditions) exert the greatest influence on interfacial bonding and dimensional accuracy in multimaterial molded components?
RQ3.2	How can AI-assisted optimization methods improve parameter selection and process robustness in industrial IM environments?
RQ4	What recent developments in digital manufacturing technologies, simulation tools, and data-driven modeling contribute to improving process understanding and optimization in MMIM?
RQ4.1	How can computational modeling and AI-driven predictive tools support the design of mold geometries, gating systems, and cooling channel configurations for enhanced process performance?
RQ4.2	What technical and practical limitations currently hinder the broader adoption of AI-assisted modeling and optimization tools in industrial IM operations?
RQ5	What are the emerging research trends and future opportunities for integrating Artificial Intelligence within MMIM processes?
RQ5.1	Which intelligent manufacturing concepts—such as smart molds, in-mold sensors, predictive maintenance systems, and closed-loop process control—show the greatest potential for advancing IM technologies?
RQ5.2	What key knowledge gaps remain regarding the integration of AI, material science, and process engineering in the development of next-generation MMIM systems?

The literature search procedure, illustrated in Figure 6 (and detailed in Figure A1), was implemented using structured Boolean queries designed to identify studies situated at the intersection of injection-molding technologies and artificial-intelligence methodologies. The search strategy incorporated combinations of search terms related to injection-molding processes and AI-based analytical techniques, including terms such as "Injection Molding", "Multimaterial Injection Molding", "Two-shot molding", "Co-injection molding", and "Multi-component molding", together with "Artificial Intelligence", "Machine Learning", "Neural Networks", "Predictive Modelling", and "Process Optimisation". This structured search approach enabled the targeted retrieval of scientific contributions directly addressing process optimisation, defect prediction, intelligent process monitoring, and data-driven decision-making in injection-molding systems, with particular relevance to multimaterial processing environments and advanced manufacturing applications.

An examination of publication records indexed within the CrossRef repository reveals a marked increase in scholarly output between 2010 and 2025, as illustrated in Figure 7. This upward trend reflects the growing academic and industrial attention devoted to the application of artificial intelligence and data-driven methodologies within IM technologies. The sustained rise in publications highlights the expanding interest in process optimization, intelligent monitoring, defect prediction, and advanced manufacturing strategies, particularly in the context of MMIM systems. Collectively, these developments underscore the increasing recognition of AI-based approaches as enabling tools for enhancing process efficiency, product quality, and overall manufacturing performance in modern polymer processing environments.

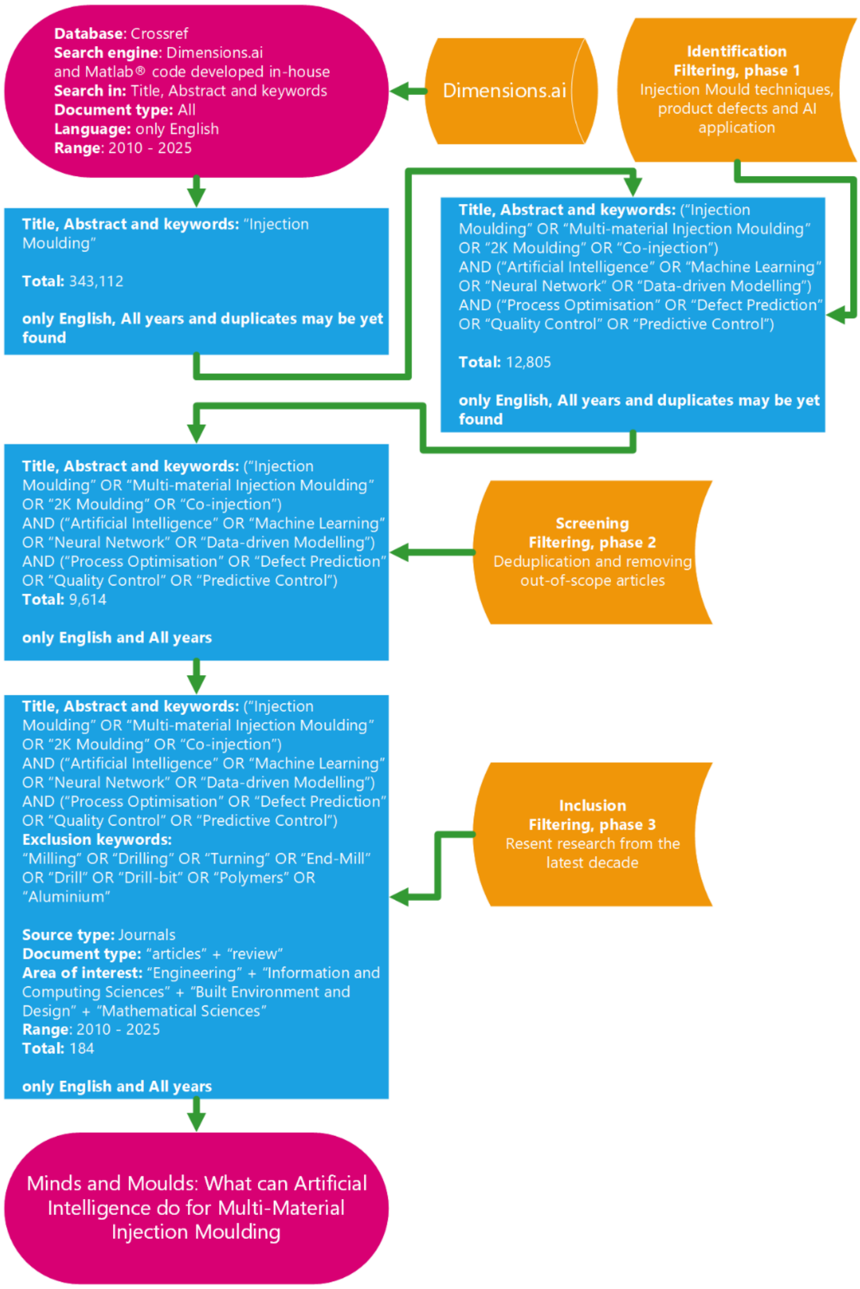


Figure 6. PRISMA-based multi-stage screening and study selection procedure applied to the literature on artificial intelligence applications in MMIM.

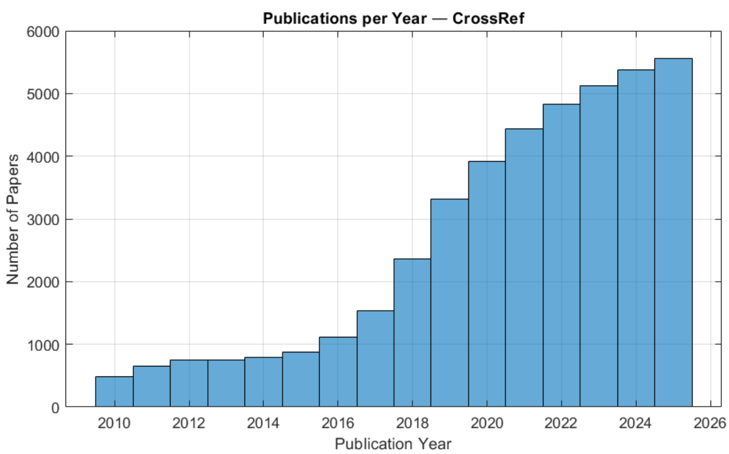


Figure 7. Annual distribution of publications retrieved from the CrossRef database related to artificial intelligence applications in IM processes.

Screening was conducted in a staged manner, proceeding from title and abstract review to full-text assessment. Initial eligibility decisions were performed independently by two reviewers using the predefined inclusion and exclusion criteria. Disagreements were resolved through discussion and, where necessary, by joint re-examination of the full text until consensus was achieved. Borderline cases were retained for full-text review to minimise premature exclusion of potentially relevant studies.

2.3. Study selection and Quality Assessment (QA)

The evaluation of methodological quality constitutes a fundamental stage in any systematic literature review, as it establishes the evidential basis upon which the reliability, validity, and interpretative strength of the subsequent analysis depend. In the present study, a structured Quality Assessment (QA) framework was developed to examine the methodological rigour, transparency, and practical relevance of each selected publication. The assessment procedure followed a multi-dimensional approach designed to capture both scientific robustness and industrial applicability within the field of MMIM and artificial intelligence–assisted manufacturing.

The QA framework comprised four equally weighted evaluation domains, each addressing a specific aspect of methodological quality and scholarly contribution. The criteria were derived from established systematic review methodologies and implemented using a three-point ordinal scoring scale, where Yes was assigned a value of 1, Partly 0.5, and No 0.

The four assessment categories were defined as follows:

- Research Design and Conceptual Framework (25%)—evaluating the clarity of the research objectives, the appropriateness of the methodological approach, and the coherence of the theoretical foundations supporting the study.
- Technical Definition of Materials and Process Parameters (25%)—assessing the extent to which IM systems, material combinations, and relevant processing variables (e.g., melt temperature, injection pressure, cooling conditions, and multimaterial interfaces) are clearly specified, including the reproducibility of the reported experimental or modeling procedures.
- Methodological Robustness and Analytical Transparency (25%)—examining the reliability of the data acquisition methods, the adequacy of modeling or validation techniques, and the overall consistency and rigour of the analytical interpretation.
- Industrial Applicability and Technological Relevance (25%)—determining the degree to which the reported findings demonstrate practical relevance for industrial IM operations, particularly regarding process optimization, defect prediction, intelligent monitoring, and AI-driven decision-making.

To maintain the reliability of the final synthesis, only studies achieving a QA score exceeding 50%, equivalent to a total score greater than 5 out of 10, were retained for further analysis, as illustrated in Figure 8. The adoption of this threshold ensured that contributions with insufficient methodological clarity were excluded while avoiding the premature elimination of studies addressing emerging artificial intelligence applications in IM, where reporting practices may vary across experimental and modeling-based research. Consequently, the QA procedure functioned primarily as a baseline reliability filter, ensuring methodological consistency while preserving the diversity of technological approaches represented within the reviewed literature.

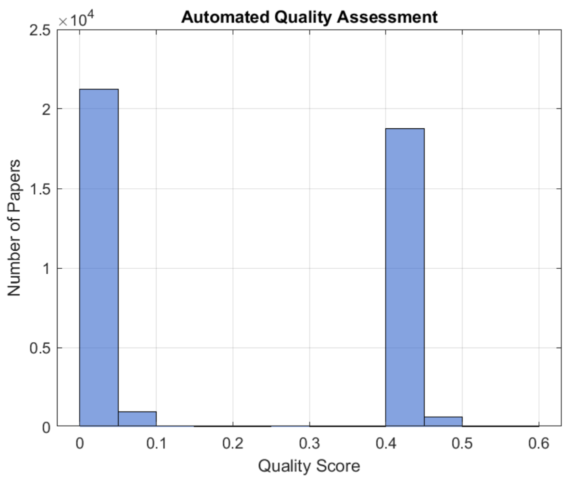


Figure 8. QA outcomes for the selected publications included in the systematic review of artificial intelligence applications in MMIM.

Publications obtaining scores close to the predefined threshold were subjected to an additional stage of qualitative examination to verify their technical relevance, methodological consistency, and alignment with the objectives of the present review. This supplementary verification ensured that borderline studies demonstrated sufficient clarity in the description of IM processes, material systems, modeling approaches, and reported outcomes before being retained. Consequently, the final body of literature comprised contributions exhibiting acceptable levels of methodological rigour, empirical relevance, and conceptual coherence, particularly with respect to process optimization, defect prediction, intelligent monitoring, and the application of artificial intelligence techniques within MMIM systems.

Studies whose QA scores fell within the borderline interval of 50–60% were re-evaluated through detailed full-text analysis conducted by the authors. This step focused on verifying the adequacy of reported process parameters, material configurations, modeling strategies, and performance indicators, thereby ensuring that only studies providing meaningful insights into AI-assisted optimization and control of IM processes were incorporated into the final synthesis.

A further methodological limitation concerns the degree of reviewer duplication during screening and quality assessment; although predefined criteria and structured re-evaluation procedures were used, full independent duplicate assessment was not implemented for the entire corpus.

The identification and selection of relevant publications followed a three-stage screening procedure consistent with the PRISMA 2020 framework, thereby ensuring a transparent and systematic progression from the initial retrieval of records to the final inclusion of eligible studies. During the first stage, all search outputs were consolidated into a unified dataset, and duplicate records were removed through a combination of automated processing and manual verification using the customised MATLAB® routine described previously.

As illustrated in Figure 9, the geographical distribution of authorship and institutional affiliation within the reviewed literature reveals a significant concentration of research activity in Europe, with the United Kingdom representing one of the most prominent contributors to the scholarly output on artificial intelligence applications in IM, process optimization, and intelligent manufacturing systems. A considerable proportion of the analyzed publications also originates from the United States, reflecting the strong industrial engagement and technological relevance associated with the development of data-driven manufacturing approaches and advanced polymer processing technologies.

This spatial distribution is noteworthy, as it demonstrates that research efforts in AI-assisted IM and intelligent manufacturing systems are not confined to a limited number of countries traditionally associated with manufacturing innovation. Instead, the field exhibits a broad and internationally distributed research landscape, highlighting the increasingly collaborative and global nature of contemporary investigations aimed at improving process efficiency, defect mitigation, material integration, and the overall performance of injection molded components through the integration of artificial intelligence techniques.

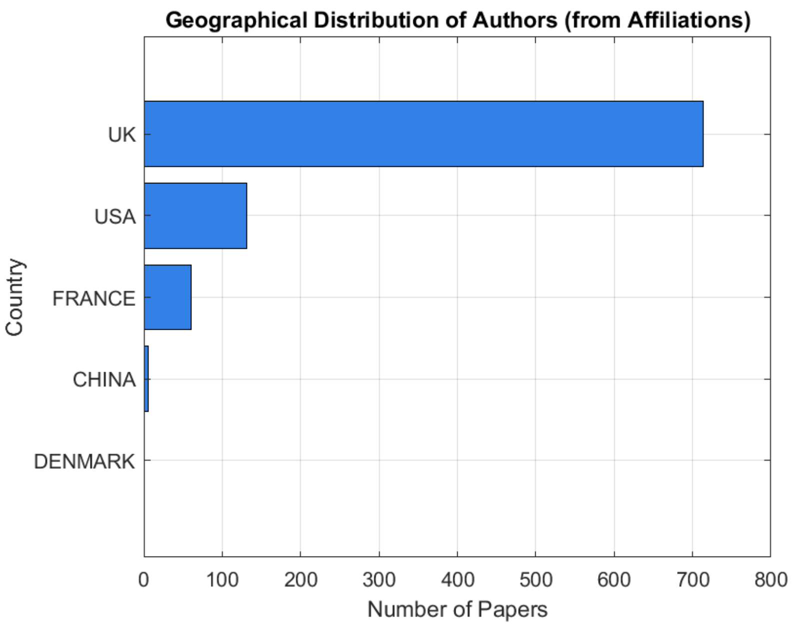


Figure 9. Geographical distribution of authors' institutional affiliations within the publications included in the systematic review.

Quality assessment was conducted using the four-domain framework described above, with each included study scored independently by two reviewers. Where scoring discrepancies arose, these were resolved by discussion and joint re-evaluation of the study against the predefined criteria. Borderline scores were examined in greater detail during full-text reassessment, particularly where methodological reporting was incomplete but the study remained technically relevant to MMIM.

2.4. Descriptive Analysis and Taxonomic Synthesis

The descriptive synthesis of the final corpus reveals a diverse and rapidly expanding research landscape, characterised by the increasing integration of polymer processing science, intelligent manufacturing technologies, and data-driven modeling approaches aimed at enhancing the reliability and efficiency of MMIM systems. The analyzed body of literature was systematically categorised according to its technological orientation, application focus, and degree of experimental or computational integration, thereby identifying the principal directions along which contemporary research in AI-assisted IM is evolving. The reviewed studies broadly converge around two interrelated research domains.

1. Multimaterial processing and material–interface behavior: This domain encompasses investigations into the behavior of polymer–polymer and hybrid multi-component material systems within IM environments. Particular attention is directed towards the interaction between material compatibility, interfacial adhesion, thermal behavior, and the mechanical integrity of molded components. Studies within this category examine the influence of processing variables—such as melt temperature, injection pressure, cooling conditions, and mold design—on the formation and stability of material interfaces in two-shot, co-injection, and over-molding processes. Research in this area seeks to improve the interfacial bonding strength, dimensional stability, and long-term functional performance of multimaterial molded products.
2. Artificial intelligence and data-driven optimization in IM: The second domain focuses on the application of artificial intelligence and machine learning techniques to improve process understanding, optimization, and control. This body of work includes studies employing artificial neural networks, evolutionary algorithms, hybrid optimization frameworks, and predictive analytics to model complex relationships between processing parameters and product quality indicators. These approaches aim to enhance parameter optimization, defect prediction, intelligent monitoring, and adaptive process control, thereby supporting the development of more efficient and reliable IM operations.

This classification highlights the inherently multidisciplinary nature of current research in intelligent polymer processing, where materials engineering, manufacturing science, data analytics, and digital manufacturing technologies converge to address the complex thermo-mechanical and rheological phenomena governing multimaterial molding processes. Across the reviewed literature, four principal thematic trajectories can be identified.

1. Defect prediction and quality improvement: A significant portion of the research focuses on identifying and mitigating common IM defects, such as weld lines, sink marks, warpage, short shots, and interfacial delamination, through the application of predictive modeling and intelligent optimization techniques. AI-based models are increasingly employed to establish correlations between process parameters and defect formation mechanisms.
2. Process parameter optimization: Another prominent research direction concerns the optimization of IM parameters in order to improve part quality, dimensional stability, and manufacturing efficiency. Data-driven models are frequently used to determine optimal combinations of parameters such as injection speed, holding pressure, melt temperature, and cooling conditions, particularly in the context of multimaterial molding where material interactions add further complexity.
3. Intelligent monitoring and process control: Recent studies explore the integration of sensor technologies, real-time data acquisition systems, and machine learning algorithms to enable adaptive and closed-loop control of IM processes. These developments form part of the broader transition towards smart manufacturing environments and Industry 4.0 paradigms.
4. Digital modeling and simulation-assisted manufacturing: Advances in simulation tools and digital modeling frameworks are increasingly combined with AI techniques to improve process prediction, mold design optimization, and process stability, thereby supporting more reliable and scalable MMIM operations.

Across the reviewed studies, several measurable performance improvements are consistently reported, which include:

- Enhanced prediction accuracy for part quality and defect occurrence, enabling improved process optimization and reduced trial-and-error experimentation.

- Improved control of process parameters, contributing to greater dimensional accuracy and more stable production conditions.
- Reduction in manufacturing defects and process variability, particularly through the implementation of predictive and adaptive control strategies.
- Improved production efficiency and reduced material waste, resulting from data-driven optimization of processing conditions.
- Greater integration of digital technologies within polymer processing environments, supporting the transition towards intelligent manufacturing systems.

Despite these advances, the literature also identifies several persistent challenges that constrain the widespread industrial deployment of AI-assisted IM technologies. These include the limited availability of high-quality industrial datasets, difficulties associated with model generalisation across different machines and materials, and the complexity of accurately modeling the nonlinear thermo-rheological behavior characteristic of polymer processing. Additional barriers include the lack of standardised benchmarking methodologies, limited interoperability between simulation tools and production equipment, and the practical challenges associated with integrating AI models within existing manufacturing infrastructures.

The review's three-stage screening procedure, implemented in accordance with the PRISMA 2020 framework, commenced with an initial evaluation of titles, abstracts, and keywords in order to identify publications relevant to IM processes, multimaterial manufacturing strategies, and artificial intelligence applications in polymer processing. This preliminary screening was followed by a full-text assessment designed to verify compliance with the predefined inclusion criteria, with particular emphasis placed on methodological robustness, empirical depth, and industrial relevance.

Only peer-reviewed journal articles were retained for the final analysis. Publications written in languages other than English, grey literature, conference abstracts lacking sufficient methodological detail, and studies without transparent analytical procedures were excluded. The resulting dataset therefore constitutes a carefully curated and scientifically robust body of literature, forming the evidential foundation for the analytical and interpretative framework developed in the present review.

3. Literature Review

The following literature review is structured to distinguish clearly between general knowledge derived from conventional injection molding and findings that are specifically relevant to MMIM [27]. General IM studies are cited only where they clarify process mechanisms, optimisation logic, defect formation pathways, or modelling approaches that remain applicable to multimaterial systems [28]. The analytical emphasis, however, is placed on evidence that illuminates the distinctive challenges of MMIM, particularly those associated with multimaterial interfaces, sequential or concurrent material injection, process stability, and AI-assisted optimisation under coupled thermo-rheological conditions [29].

3.1. MMIM Techniques

The multi-component IM technique is used to produce polymer parts consisting of multiple, different or in some cases equal materials within a single IM machine. The main goal of this technique is combining properties of multiple materials in a single product [30].

A typical multi-component IM machine has one clamping unit holding the multi-component mold, and at least two injection units. In most applications, the main injection unit is placed horizontally. The second unit is often placed in a vertical or horizontal position on top of the IM machine. Another option is to add the second unit under an angle above the first injection unit [31].

Today, different multi-component IM techniques exist. These are bi-injection molding, co-injection molding, multi-shot injection molding and insert over molding. The applied technique depends on the injection molded [32,33].

3.1.1. Bi-injection

A bi-injection molding process involves the injection of two different components, different materials or different colours, into a mold having a separate injection location [31]. The flow of both materials is independently controlled by two different injection units. Like all multi-component IM techniques, the bi-injection processes use two barrels and two nozzles in one IM machine [32,33]. The procedure of the bi-injection process is shown in Figure 10. In the bi- IM process, the injection of both components can be at the same moment, which results in a reduction in cycle time compared to other multi component IM techniques. However, this also results in a less controllable interface between both components [32,33]. Table 2 summarises some of the found literature on the field regarding bi-injection.

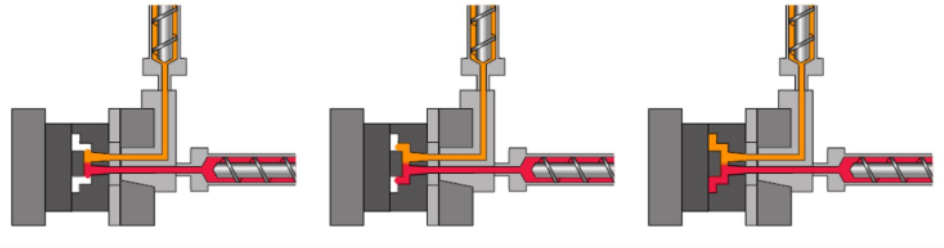


Figure 10. Bi-injection molding procedure [31].

Table 2. Studies carries out on bi-injection molding.

References	Challenges	Highlights
Cao et al. [34]	Coordinated control of dual melt injections	Develops a dynamic modeling and control framework for bi-injection molding where two polymer melts are simultaneously injected through separate gates, enabling coordinated regulation of injection velocities and improved stability of multimaterial filling behavior.
Ou et al. [35]	Coupled thermo-rheological and curing phenomena	Develops a multiphysics thermo-rheo-kinetic modeling framework for thermoplastic–liquid silicone rubber bi-injection molding, integrating rheological characterisation, curing kinetics, and finite-element simulation to accurately predict filling behavior, temperature evolution, and curing progression
Sahli et al. [36]	Complex thermo-rheo-kinetic behavior and interface adhesion modeling	Experimental and finite element investigations of PA66–LSR bi-injection molding demonstrated accurate prediction of flow behavior, curing kinetics, temperature distribution, and interfacial adhesion, with simulation results closely matching experimental measurements (error < 3%).
Barrière et al. [37]	Coupled rheology and curing in bi-injection.	Combines rheological characterisation, curing kinetics modeling, and finite-element simulation to analyze thermoplastic–LSR bi-injection molding, demonstrating accurate prediction of filling behavior, curing evolution, and interfacial integrity with strong agreement between numerical and experimental results.
Özel and Soylemez [38]	Interfacial adhesion control in bi-injection	Experimental and numerical investigation of two-shot bi-injection molding demonstrates that interface temperature relative to glass transition governs polymer interdiffusion and bond strength, enabling near single-material mechanical performance through optimised melt temperature and process control.

3.1.2. Co-Injection Molding

Co-Injection Molding is also known as dual injection, sandwich molding, 2K or 3K. This involves making sequential injections into the same mold with one material as the core and another as the skin. It can be recognized by the production of a defined skin and core structure. The core is fully encapsulated, to produce a sandwich like molding [20]. The co-injection molding process, presented in Figure 11 involves the injection of two dissimilar materials via the same injection location. The sequential co-injection process uses an IM machine with two barrels and one nozzle [31].

The process comprises of three phases. In the first phase, the skin plastic is injected into the mold. In this phase, only a fraction of the mold is filled. In the second phase, the core plastic is injected. The process is completed when the skin plastic is injected again. This step purges the core material from the sprue and completes the skin of the product. The skin plastic is the material expected to be deposited on the cavity wall over the entire surface of the part [32,33]. Table 3 summarises some of the found literature on the field regarding co-injection.

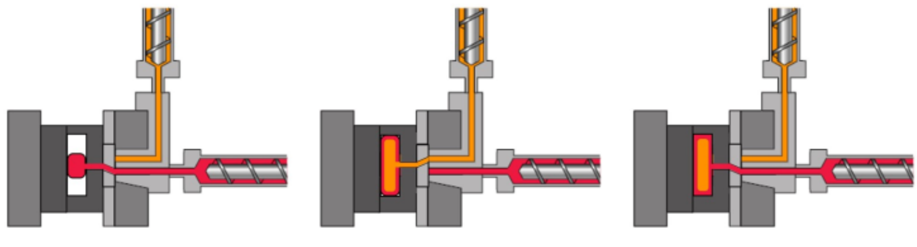


Figure 11. Fountain flow effect used in the co-injection molding process (adapted from [32,33]).

Table 3. Studies carried out on co-injection molding.

References	Challenges	Highlights
Lu et al. [39]	Controlling micro-morphology during co-injection	Demonstrates that co-injection molding can produce self-reinforced single-polymer composites with significantly enhanced mechanical performance. Process parameter manipulation governs micro-morphology, molecular orientation, and skin–core architecture, enabling tensile strength improvements approaching 24%.
Lu et al. [40]	Modeling rheology in slender runners	Develops a cross-scale rheological model describing melt flow behavior during in-mold co-injection in slender channels. Experimental visualisation and modeling demonstrate how micro-scale runner geometry influences viscosity, temperature distribution, and flow dynamics, significantly improving simulation accuracy for predicting co-injection filling behavior
Gall et al. [41]	Recyclate contamination affecting structural integrity	Demonstrates the feasibility of co-injection molding to incorporate post-consumer polypropylene as a core layer within sandwich-structured components. While recycled inclusions influence toughness and impact resistance, stiffness-controlled performance and load-bearing capacity remain comparable or improved, highlighting the viability of recycled cores for structurally demanding products when appropriate design-from-recycling strategies are adopted.
Huang et al. [42]	Predicting skin–core morphology evolution	Combined numerical simulation and experimental validation reveal the formation mechanism of a previously unreported Core–Skin–Core (CSC) morphology in two-stage co-injection molding. The study shows that appropriate skin-to-core ratios induce CSC structures through skin breakthrough and fountain-flow dynamics, while processing parameters exert minimal influence once the structure forms
He et al. [43]	Skin–core viscosity mismatch during co-injection	Experimental and simulation study of SEBS/PP co-injection molding introducing a dynamic viscosity ratio approach to evaluate filling behavior and optimise interface matching, enabling smoother flow fronts, improved skin–core bonding, and enhanced filling stability.
Liu et al. [44]	Predicting and controlling surface defects.	Comprehensive review of high surface quality IM, analyzing measurement techniques, defect mechanisms, prediction approaches, and process control strategies influencing gloss, texture, and optical appearance of molded polymer components.
Wang et al. [45]	Controlling cell morphology in co-injection foaming	Demonstrates that co-injection foaming of iPP/HDPE composites produces a dense skin–foamed core structure with improved surface quality and mechanical performance. Optimised HDPE content, foaming agent concentration, and nanoclay nucleation significantly refine cell structure and enhance impact resistance.
Wieczorek et al. [46]	Core-layer thickness control in co-injection	Investigates co-injection molding of three-layer thin-wall packaging using recycled r(PP+EVOH) as the core material, demonstrating controlled multilayer distribution and confirming that up to 50 vol% recycled content can be incorporated while maintaining acceptable mechanical performance.
Kuang et al. [47]	Wall thickness uniformity in co-injection pipes	Experimental evaluation of fluid-projectile-assisted co-injection molding for glass-fibre-reinforced PP composite pipes demonstrates improved wall-thickness uniformity, enhanced fibre orientation, and superior pressure resistance when the overflow co-injection strategy is employed.
Shen and Ren [48]	Complex sequencing in multimaterial co-injection	Proposes a three-color molding strategy combining dual-color co-injection and subsequent overmolding to integrate ABS, PMMA, and TPS within a single automotive component, supported by Moldflow simulation and optimised cooling design to minimise warpage and ensure dimensional accuracy.
Huang et al. [49]	Multiphase flow instability in co-injection	Experimental and CFD investigation of gas-assisted co-injection molding of PP–HDPE tubular components, demonstrating how melt injection sequence, filling method, and cavity diameter govern gas penetration behavior, interface stability, and residual wall thickness distribution in multilayer structures.

3.1.3. Multi-Shot IM

Multi-shot IM has been made possible by advances in polymer materials and mold technology. For this process, specialized IM machines have been developed since the 1960s [32,33,50]. The multi-shot IM process is very similar to combining two or multiple standard IM processes in a sequential way, as depicted in Figure 12. Multi-shot IM using two components is often abbreviated as 2K IM. The process starts with the injection of the first component. After a sufficient cooling time, the product is over molded with the second component [20].

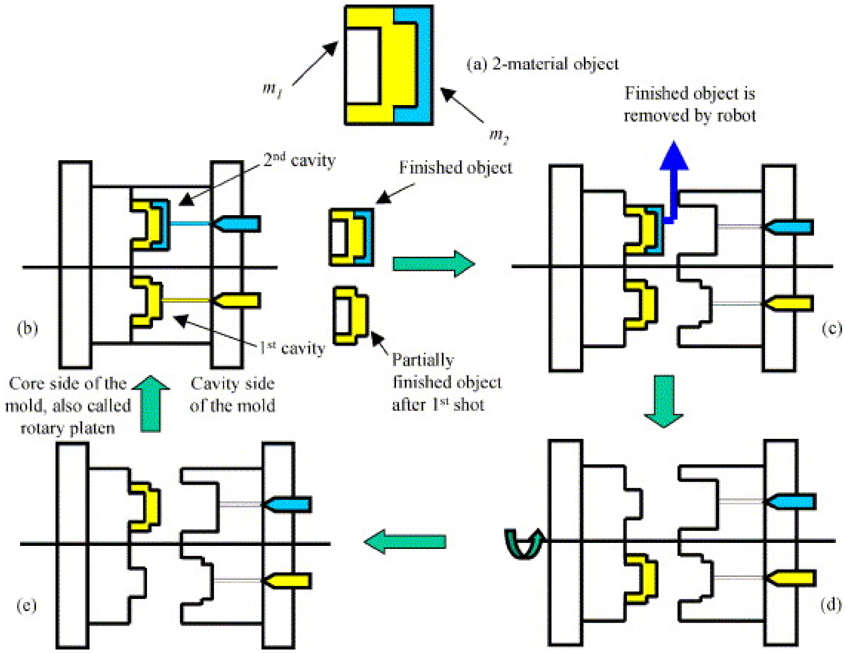


Figure 12. Rotary-platen type two-shot IM process: (**a**) Two-material molded object, (**b**) First and second injection positions, (**c**) Part removal after second shot, (**d**) Rotation of the platen, (**e**) Mold ready for the next cycle [50].

Next to the demand for advanced IM machines, specialized mold techniques are needed to move the components between cavities. The technique of cavity transfer will be discussed later. Currently, up to four components in one mold are possible using specialized indexing techniques. Although possible, adding extra components in one mold increases mold and machine costs [20]. Table 4 summarises some of the found literature on the field regarding multi-shot IM.

Table 4. Studies carried out on multi-shot technique in IM.

References	Challenges	Highlights
Wang et al. [51]	Uniform shrinkage across multi-shot layers	Demonstrates that multi-shot injection molding of an aspherical Blu-ray objective lens reduces shrinkage-induced displacement relative to single-shot molding, improves form accuracy, and shortens cooling time, thereby enhancing dimensional precision in micro-optical component manufacture.
Schneider et al. [52]	Precise sequencing of consecutive shots	Demonstrates that multi-shot injection molding enables sequential introduction of distinct melts within a single cycle to generate controlled skin–core architectures, using modular inserts and intermediate plates to extend standard machine capability.
Tengsuthiwat et al. [53]	Precise sequencing of plateable shots	Identifies two-shot injection molding as a key route in 3D-MID manufacture, enabling complex three-dimensional circuitry through sequential molding of non-plateable and plateable polymers with high geometric freedom and production precision.
Gim and Turng [54]	Surface defects and bubble exposure in foamed parts	Describes co-injection molding strategies enabling a solid polymer skin and foamed core architecture, preventing surface bubble exposure while maintaining lightweight structures, thereby significantly improving surface quality and structural integrity of molded components

Table 4. Studies carried out on multi-shot technique in IM.

References	Challenges	Highlights
Dias et al. [55]	Material compatibility and complex two-shot tooling	Reviews two-shot injection molding as a multi-component route for integrating lightweight microcellular cores with decorative or functional outer layers, enabling defect masking, improved interfacial bonding, reduced assembly operations, and enhanced product value.
Gao et al. [56]	Shrinkage and birefringence in thick optics	Proposes a multilayer IM process enabling sequential layer deposition for ultra-thick transparent polymer optics, combining cooling-time modeling, bidirectional injection strategies, and parameter optimization to significantly reduce shrinkage deformation and birefringence.
Czepiel et al. [57]	Complex tooling for multicomponent processing	Reviews multi-shot as a multicomponent injection-molding route enabling one-cycle manufacture of multicolour and multifunctional parts from materials with dissimilar mechanical properties, particularly rigid thermoplastics combined with softer elastomeric phases.

3.1.4. Over-Molding

Over-Molding technique is where components are placed in an injection mold and are then molded over with another material. The term over-molding covers both insert molding and lost core molding; the latter produces a hollow component. This technique is not confined to plastics and over-molding of metal inserts, such as to produce scissor handles, and on ceramics is commonplace [20]. Figure 13 depicts an overmolded condition.

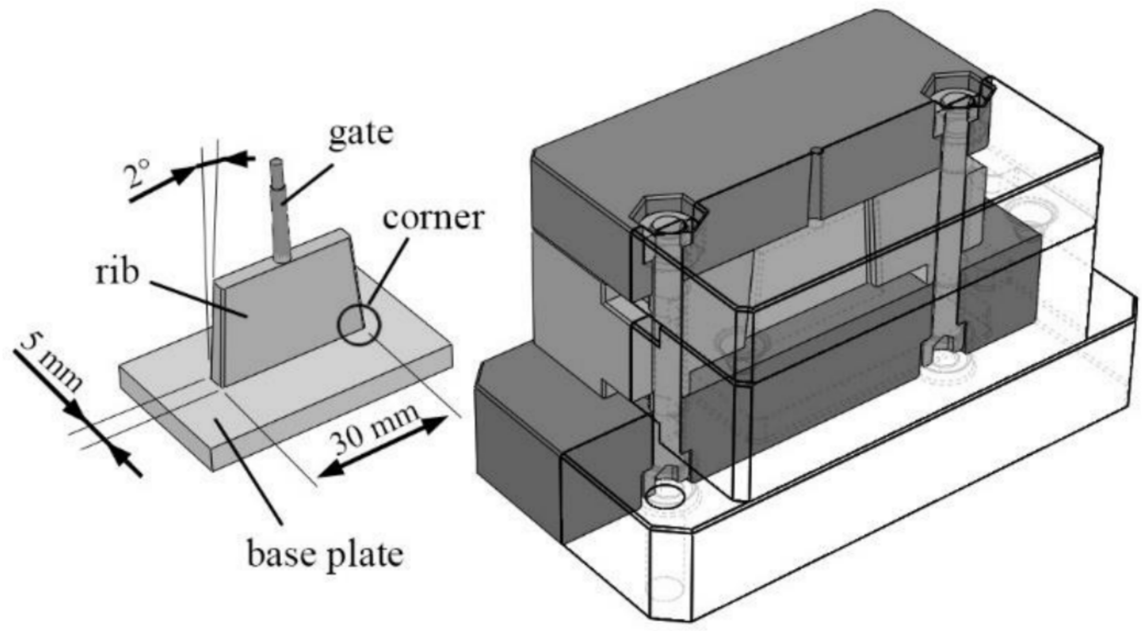


Figure 13. The mold and the molded component: (**left**) the molding configuration, comprising a base plate over-molded with a rib through the gate; (**right**) the aluminium prototype mold of three-plate configuration, partially transparent [58].

Although classified as a multi-component IM process, the insert over-molding process does not imply two IM units on the same IM machine. The insert defined in this over-molding technique is not injected in the mold but is placed in the mold as a separate, pre-produced component. This component can be a polymer, a metal, or a ceramic part [59]. Table 5 summarises some of the found literature on the field regarding the over-molding technique.

Table 5. Studies carried out on over-molding technique.

References	Challenges	Highlights
Lafranche et al. [60]	Rapid cooling limiting interfacial diffusion	Examines thin-wall injection over-molding of PA6 onto PP-g-MA multilayer structures, demonstrating that adhesion is governed by pressure-dependent wettability, interdiffusion, and reactive grafting, leading to copolymer interphase formation that significantly enhances peel resistance and mechanical performance.
Liese et al. [61]	Achieving uniform thin polymer layer adhesion	Investigates over-molding of additively manufactured Ti6Al4V inserts with tribologically optimised POM, demonstrating that insert surface roughness, build orientation, and polymer filler composition significantly influence interfacial bonding and peeling resistance in polymer–metal hybrid components.
Wurzbacher et al. [62]	Reliable polymer–metal interfacial bonding mechanisms	Demonstrates that plastic–metal hybrid components can be effectively joined by over-molding electron-beam-generated micro form-fit structures, where joint strength arises from the combined contribution of elevations, indentations, and their interaction within the molded interface.
Aliyeva et al. [63]	Interfacial adhesion between dissimilar materials	Provides a comprehensive review of over-molding technologies for thermoplastic and thermoset composite systems, emphasising multimaterial injection and insert molding, reinforcement strategies from nano- to macro-scale, and process optimization for improved bonding, lightweight structures, and multifunctional composite manufacturing.
Le Mouellic et al. [64]	Polymer–polymer interfacial heat transfer characterisation	Develops an instrumented over-molding apparatus enabling non-intrusive measurement of heat flux and surface temperatures at TPV/TPV interfaces, allowing experimental determination of thermal contact resistance and its evolution during crystallisation and cooling.
Hannesschläger et al. [65]	Precise alignment during over-molding processes	Introduces an in-mold optical coherence tomography (OCT) sensing system integrated with a piezo-actuated positioning device, enabling real-time detection and correction of alignment errors during over-molding of optoelectronic components with micrometre-scale accuracy.
Aliyeva et al. [66]	Weak fibre–matrix adhesion; moisture sensitivity	Develops a sustainable hybrid composite manufacturing strategy integrating injection molding with over-molding using hemp fibre/GNP-reinforced polypropylene and UD flax prepreg inserts, significantly enhancing tensile, flexural, and impact properties while reducing component weight and environmental footprint.
Wang et al. [67]	Tape consolidation and fibre waviness control	Demonstrates that over-molding of UD carbon-fibre thermoplastic tapes within long-fibre polypropylene matrices significantly enhances flexural stiffness and load capacity while reducing voids and surface undulations, improving structural performance of hybrid injection-molded components
Parsons et al. [68]	Interfacial stress transfer and bonding	Demonstrates that thermoplastic composite over-molding enables integration of continuous fibre inserts within injection-molded short-fibre matrices, providing structural reinforcement while maintaining high-rate manufacturing and enabling cost-efficient hybrid composite component design.
Shen and Ren [48]	Reliable bonding in over-molded multimaterial parts	Demonstrates an over-molding strategy for integrating a soft TPS layer onto previously molded rigid ABS–PMMA substrates within an automotive trim component, enabling functional sealing, improved structural integration, and reduced assembly steps through multimaterial mold consolidation.

3.2. IM phases of specific relevance to MMIM

The standard IM process are controlled by four main phases: plasticization, filling, packing and solidification [20].

The principal stages of the injection-molding cycle—plasticisation, filling, packing, and solidification—are well established in conventional IM. In MMIM, however, these stages require a more selective interpretation, because the interaction between dissimilar materials introduces additional constraints not present in single-material processing. In particular, the evolution of the material interface, differences in viscosity and thermal history, sequence-dependent filling behaviour, and differential shrinkage during cooling can substantially modify the process window and defect sensitivity. For this reason, the following discussion considers each phase only insofar as it contributes to understanding MMIM-specific optimisation challenges and the potential role of AI in addressing them.

3.2.1. Plasticization

In the first phase, plasticization is the action melting the feedstock. The polymer flow rate is governed by the material process conditions of the plasticization stage and is a combination of material rheology, barrel temperature, shear, back pressure, and screw speed. The basic aim is to pass the plastic in the solid to liquid for the next stage where the material enters the mold [20]. Table 6 summarises some of the found literature on the field regarding challenges with plasticization. In MMIM, plasticisation is particularly significant because differences in melt rheology, thermal sensitivity, and material compatibility can influence the stability of subsequent interface formation. Unless otherwise stated, the studies summarised below are included because their underlying process mechanisms are transferable to MMIM and help to explain defect formation, parameter sensitivity, or optimisation pathways in multimaterial molding environments.

Table 6. Studies carried out regarding plasticization challenges.

References	Challenges	Highlights
Wu et al. [69]	Controlling transient interfacial friction plasticisation	Demonstrates that ultrasonic plasticisation is governed by a rapid, localised interfacial friction-heating stage, with ultrasonic amplitude exerting greater influence than plasticising pressure on heating rate and early melt formation.
Iwko et al. [70]	Accurate modeling of reciprocating-screw plasticisation	Develops and experimentally verifies a comprehensive mathematical model of injection-molding plasticisation, capturing solid-bed evolution, pressure and temperature profiles, screw torque, power demand, and recovery time with average prediction errors below 10%.
Peng et al. [71]	Uneven ultrasonic plasticisation and overheating	Demonstrates that plasticisation in ultrasonic plasticisation injection molding begins with a transient interfacial friction-heating stage, strongly governed by ultrasonic amplitude and frequency, with rapid local temperature rise controlling melt initiation and process stability.
Chen et al. [72]	Moisture-sensitive plasticisation under hygroscopic conditions	Demonstrates that optimising plasticisation variables—lower screw speed and barrel temperature with higher back pressure—suppresses moisture-induced bubbles and silver streaks, enabling reduced drying time while preserving high surface gloss in hygroscopic polymers.
Wu et al. [73]	Quantifying plasticisation-rate evolution under ultrasound	Establishes a rod-based measurement method for ultrasonic plasticisation, demonstrating that increasing amplitude markedly accelerates plasticisation while preserving tensile performance and improving crystallinity, crystallisation behavior, and thermal stability of polypropylene.
Pan et al. [74]	Maintaining melt fluidity during ultrasonic plasticisation	Demonstrates that ultrasonic plasticisation markedly lowers polypropylene melt viscosity, particularly at higher amplitudes, thereby enhancing melt flow and enabling high-fidelity replication of deep microstructures, reaching 238.2 μm with 97.4% replication fidelity.
Gülçür et al. [75]	Balancing interfacial friction and plasticisation	Demonstrates that ultrasonic plasticisation is strongly governed by feedstock geometry, with pellet feedstocks providing the most favourable balance between interfacial friction and viscoelastic heating, thereby improving viscosity reduction, process repeatability, and micro-feature replication.
Hopmann and Wolters [76]	Severe fibre attrition during plasticisation	Demonstrates that thermoplastic foam injection molding under a constant blowing-agent atmosphere mitigates fibre damage during plasticisation by reducing melt viscosity and altering melting behavior, thereby preserving fibre length and improving fibre-length distribution.
Wu et al. [77]	Process-dependent melt plasticisation stability	Compares three ultrasonic plasticisation molding routes and demonstrates that plasticisation configuration strongly governs melt temperature, pressure, and sustained fluidity; continuous sonotrode coverage during plasticisation and filling yields superior melt stability and microstructure formation.

3.2.2. Filling

The filling phase initiates with the forward movement of the spindle, compelling the moulten material to traverse the feed channels towards the mold cavity. Upon reaching the cavity, a small flow front of moulten plastic material is generated. As this moulten material contacts the mold walls, it starts to solidify due to the lower temperature compared to the melt. Consequently, a solid layer forms in contact with the mold wall while the core retains its moulten state. Figure 14 shows the filling of a mold cavity. In MMIM, the filling stage is not only a question of cavity completion, but also of controlling flow-front interaction, sequence-dependent material placement, and the development of a stable and functionally appropriate interface between dissimilar melts.

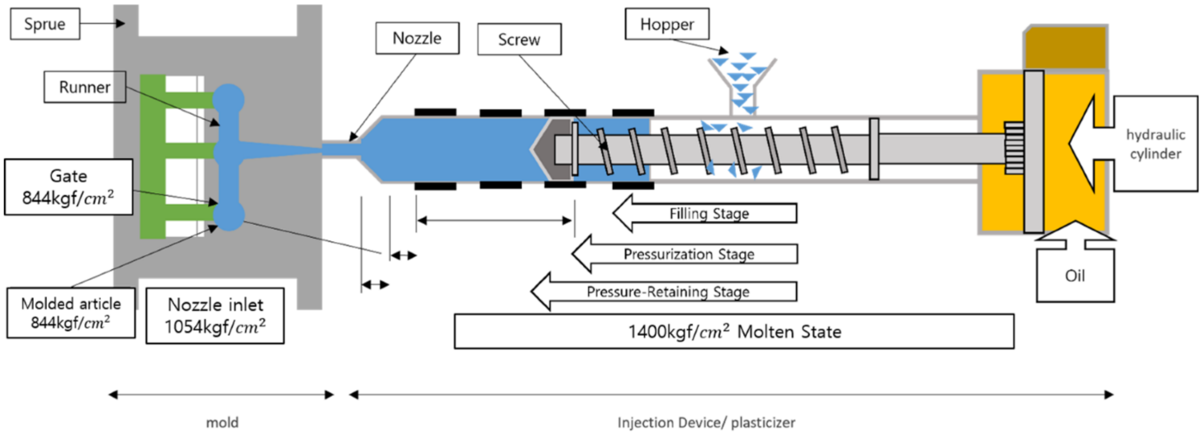


Figure 14. Structural configuration of the injection molding process [58].

The continuous injection of material compels this moulten core to flow along the mold, propelling the movement of the flow front [78]. Table 7 summarises some of the found literature on the field regarding challenges on IM filling.

Table 7. Studies carried out regarding filling challenges.

References	Challenges	Highlights
Tromm et al. [79]	Controlling premature cell evolution during filling	Demonstrates that mold filling in high-pressure foam injection molding governs premature cell nucleation, deformation, and dissolution; optimised packing conditions enable complete re-dissolution before mold opening, producing finer and more uniform final cellular structures.
Yu et al. [80]	Non-uniform filling across micro-arrays	Demonstrates that filling of PLA micropillar arrays in microinjection molding is governed by injection-velocity-dependent thermal retention and pressure rise at wall impingement, which unexpectedly favours more complete filling of distal microcavities.
Ma and Fu [81]	Stable mold filling with suspension agents	Demonstrates that, despite modest flow hindrance from the suspension agent, lost-foam suspension casting maintains stable, turbulence-free mold filling, while controlled air-gap evolution and thermal conditions preserve fluidity and support defect-minimised cavity completion.
Yavari and Alizadeh [82]	Avoiding segregation during mold filling	Demonstrates that low-pressure injection mold filling of alumina-based feedstocks remains balanced across twin cavities, but higher flow rates intensify powder–binder segregation; optimised formulations and lower flow rates provide the most stable filling behavior.
Karl et al. [83]	Capturing flow–fibre coupling during filling	Demonstrates that flow–fibre coupling during mold filling substantially modifies fibre orientation and, consequently, the post-solidification stress field in short-fibre-reinforced composites, thereby justifying coupled non-Newtonian simulation for reliable structural prediction.
Chien et al. [84]	Filling imbalance in multi-cavity molds	Demonstrates that filling behavior in geometrically balanced multi-cavity injection molds is strongly governed by runner size, gate size, polymer viscosity, and molding method; larger gates improve balance, while microcellular foaming can mitigate thermal-flow asymmetry.
Rabhi et al. [85]	Friction-limited micro-cavity filling accuracy	Demonstrates that accurate filling prediction in micro hot embossing requires an elastic–viscoplastic constitutive model; imposed displacement and embossing temperature dominate filling efficiency, while friction exerts a secondary but measurable constraint on complete cavity replication.
Uyen et al. [86]	Stable filling of thin-wall cavities	Demonstrates that integrating a cooling layer within a thin-walled insert mold improves thermal uniformity, reduces local temperature gradients, and enhances cavity filling stability and completeness, particularly under moderate injection-pressure conditions.
Li et al. [87]	Achieving complete filling of lens arrays	Demonstrates that filling in precision glass molding is governed principally by molding temperature and pressure; D-K9 ring-array lenses achieved approximately 99.5% filling at 590 °C, 1 kN, and 30 s.
Li et al. [88]	Incomplete filling under high slurry viscosity	Demonstrates that mold filling of semi-solid 6061 aluminium slurry is governed by inner-gate velocity, shear-stress distribution, and pressure drop, enabling complete lens-bracket formation with dimensional errors below 0.18 mm under optimised conditions.

The parameters of mold filling are of great importance to the quality of the finished article especially when considering factors such as warpage (orientation effects) and surface finish (skin formation) [20].

Filling dynamics are considered a significant factor influencing residual stress levels. Maintaining reproducible injection speeds is essential, as even slight variations can lead to product inconsistencies. Excessively high injection speeds may result in issues like jetting, where the melt fails to adhere to the tool and degradation, adversely affecting mechanical properties. Conversely, low speeds can increase injection pressure requirements due to a thicker frozen layer, as moulten material cools more slowly, necessitating higher pressures to push additional material behind it. This situation can lead to incomplete filling of the mold, commonly known as short shots [20].

3.2.3. Packing

Packing is the third phase, usually begins when the volume of material injected is close to 95% of the total volume to be injected. It is marked by a change in the equipment's operating regime, which moves from a dynamic control phase (injection speed) to a pressure control phase. It is with compaction that the effects of material contraction due to cooling are reduced, achieving better results in terms of warping. However, excessive compaction pressures can cause damage to the part, particularly the development of internal stresses [89].

This phase ends as soon as the material entering the molding cavities or the part itself has cooled sufficiently to inhibit the flow of material [90]. Table 8 summarises some of the found literature on the field regarding challenges on IM packing. For MMIM systems, packing conditions additionally influence interfacial stress development, local material redistribution, and the dimensional compatibility of the combined material domains.

Table 8. Studies carried out regarding packing challenges.

References	Challenges	Highlights
Wee et al. [91]	Optimising packing-pressure-induced surface structure	Demonstrates that packing pressure significantly alters surface molecular orientation and residual stress, thereby governing scratch visibility and damage-transition behavior in glass-fibre-reinforced polycarbonate, with intermediate packing conditions offering the most favourable surface resistance.
Kitayama et al. [92]	Optimising variable packing-pressure trajectories	Demonstrates that variable packing-pressure profiles can simultaneously reduce warpage and cycle time relative to constant-pressure packing, with numerical optimization and experimental validation confirming improved dimensional accuracy and productivity.
Zhao et al. [93]	Predicting crystallinity during packing stage	Proposes a simulation-based method linking packing-stage pressure, temperature, PVT-derived density, and crystallinity, enabling evaluation of how mold temperature, packing pressure, and packing time govern crystallisation behavior in injection-molded polymers.
Tseng et al. [94]	Capturing packing-induced fibre orientation evolution	Demonstrates that the packing stage materially alters shell–core fibre orientation in long glass-fibre composites, narrowing the core through packing-induced core flow and viscosity gradients, with packing pressure exerting greater influence than packing time
Chen et al. [95]	Precise filling-to-packing switchover determination	Demonstrates that tie-bar elongation profiles can reliably identify filling-to-packing transition and packing behavior without invasive cavity sensors, enabling improved process stability, part-weight consistency, and practical real-time quality control in injection molding.
Kitayama et al. [96]	Balancing packing profile and cycle time	Demonstrates that a variable packing-pressure profile in rapid heat cycle molding—low initially, higher towards the end of packing—improves melt flow, reduces weld-line formation, lowers clamping force, and shortens cycle time
Xu et al. [97]	Packing adaptation under viscosity fluctuations	Develops a real-time viscosity-compensation strategy that uses pressure–time integrals to detect melt-viscosity changes and automatically adjust V/P switchover and packing pressure, reducing part-weight variation by 50–70%.
Estrella-Guayasamin et al. [98]	Packing-pressure effects on residual-stress development	Demonstrates that packing pressure strongly governs pressure-induced residual stresses and post-ejection deflection in injection-molded polypropylene; an intermediate packing level minimises deformation, whereas excessive packing intensifies stress relaxation and dimensional instability.
Sun et al. [99]	Controlling dense packing of platelet fillers	Demonstrates that dense packing drives high-aspect-ratio flakes from locally isotropic to anisotropic organization, while injection molding converts this into global alignment, enabling shape-controllable composites with markedly enhanced thermal conductivity.

3.2.4. Solidification

Solidification is the phase of the cycle characterised by the exchange of heat carried by the material. It depends mainly on the thickness of the part, the design of the mold, the coolant and its temperature, and the temperature of the casting [100,101]. This is the most time-consuming phase of the molding cycle, beginning with filling and ending when the part has reached a temperature that allows it to be molded without distortion. In multimaterial components, solidification must also be interpreted in relation to differential cooling rates, mismatched shrinkage behaviour, and the emergence of residual stresses at the material interface.

Cooling is then responsible for reducing the internal stresses caused by compaction, but results in a significant increase in cycle time [100,101].

Cooling constitutes a significant portion, ranging from 50% to 80% of the total molding time across the four stages of the IM process [101]. Hence, it is crucial to minimize cooling time to reduce the overall cycle time, as efficiency and productivity are closely tied to it. Various methods have been employed to decrease cooling time and enhance productivity, thereby improving profitability. One strategy to achieve a reduction in molding time involves the implementation of conformal cooling/heating channels. These channels conform to the geometry/shape of the cavity, enabling a faster and more uniform decrease in the part's temperature. By ensuring uniform coolant access to all part locations, these channels contribute to efficient and consistent product quality [7,102]. The utilization of artificial intelligence techniques in the micro IM process enables rapid heating and cooling, thereby enhancing product quality and reducing molding time [103]. Table 9 summarises some of the found literature on the field regarding challenges on IM solidification phase.

Table 9. Studies carried out regarding solidification challenges.

References	Challenges	Highlights
Azaman et al. [104]	Non-uniform solidification inducing residual stresses	Numerical simulation of thin-walled polypropylene injection molding demonstrates that solidification governs residual stress development and volumetric shrinkage. Fibre and wood fillers modify thermal expansion and crystallisation behavior, influencing shrinkage gradients and consequently controlling warpage behavior in molded components.
Hopmann and Schmitz [105]	Non-uniform solidification causing dimensional distortion	Proposes a segmented mold temperature control strategy enabling localised thermal regulation during injection molding. By dynamically adjusting mold surface temperature, the approach improves melt solidification control, reduces differential shrinkage, and significantly mitigates part warpage.
Luca and Riemer [106]	Rapid solidification restricting micro-cavity filling	Demonstrates that downscaling in micro-injection molding significantly accelerates melt solidification due to high surface-to-volume ratios, constraining achievable flow length. The study correlates process fingerprints with flow behavior, enabling predictive quality control and improved process monitoring.
[107]	Dynamic pressure-induced melt solidification control	Demonstrates that polymer melt solidification depends not only on temperature and pressure, but also on compression rate during flow. The study establishes a dynamic no-flow criterion and a master-curve description relevant to simulation of thin-walled and microstructured injection-molded components.
Liparoti et al. [108]	Premature melt solidification during cavity filling	The study develops a simplified modeling framework to predict melt advancement and solidification in thin micro-injection molded parts, linking flow length to rheological parameters, pressure conditions, and frozen-layer growth during cooling.
Li et al. [109]	Shear-induced morphology during melt solidification	Injection molding induces coupled shear flow and thermal gradients during melt solidification, generating a pronounced skin–core morphology with preferential nanoplatelet alignment and reduced microphase separation, thereby enhancing structural density, mechanical performance, and barrier behavior in SEBS nanocomposites.
Liparoti et al. [110]	Crystallisation–viscosity coupling during solidification	Develops a multi-scale simulation framework linking macro-cavity filling with micro-feature replication, emphasising the influence of crystallisation and rheological behavior on melt solidification. The study demonstrates how cavity temperature and viscosity modeling govern solidification kinetics and replication accuracy in micro-structured injection-molded parts.
Chen et al. [111]	Complex crystallisation-driven solidification monitoring	Introduces an in-mold monitoring approach using infrared melt-temperature sensing to detect crystallisation completion and solidification behavior in crystalline polymers. Predictive models linking crystallisation time and time-averaged cavity pressure enable improved shrinkage control and reduced warpage in injection-molded parts.
Chang et al. [112]	Poorly characterised bulk viscoelastic solidification behavior	Demonstrates that bulk viscosity significantly influences pressure evolution and volumetric shrinkage during polymer solidification in injection molding. A three-element constitutive model improves prediction of cavity pressure, part weight, and shrinkage compared with conventional GNF approaches.
Nathan and Prabhu [113]	Air gap formation during solidification	Experimental investigation quantifies interfacial heat flux and heat transfer coefficients during polymer solidification in injection molding. Results demonstrate that air-gap nucleation significantly alters interfacial heat transfer, influencing cooling kinetics, polymer skin formation, and solidification behavior.

3.3. Process Parameters and Defect Mechanisms of Specific Relevance to MMIM

Although many of the governing variables in MMIM are inherited from conventional injection molding, their optimisation becomes more complex when two or more materials must be processed within a single cycle. In MMIM, parameter selection affects not only the behaviour of each individual material, but also interfacial integrity, sequence stability, dimensional compatibility, and the risk of multimaterial defect formation [32,33].

Accordingly, the present section focuses on those process parameters and defect mechanisms that are most relevant to the performance, reliability, and optimisation of multimaterial molded components. Defects such as weld lines, sink marks, short shots, warpage, burn marks, and interfacial failure are therefore discussed not merely as generic injection-molding imperfections, but as optimisation-relevant failure modes whose severity may be amplified or modified in MMIM by dissimilar material behaviour and greater process complexity [32,33]. Unless otherwise stated, the studies summarised below are included because their underlying process mechanisms are transferable to MMIM and help to explain defect formation, parameter sensitivity, or optimisation pathways in multimaterial molding environments.

3.3.1. Weak Weld-Line Strength

Weak weld-line strength can be caused by one of the following factors. For instance, a low temperature can hinder the proper bonding of plastic across a weld line, either due to the temperature itself or the cold surface of the mold [114]. Figure 15 depicts an example of a weld line in a IM product.

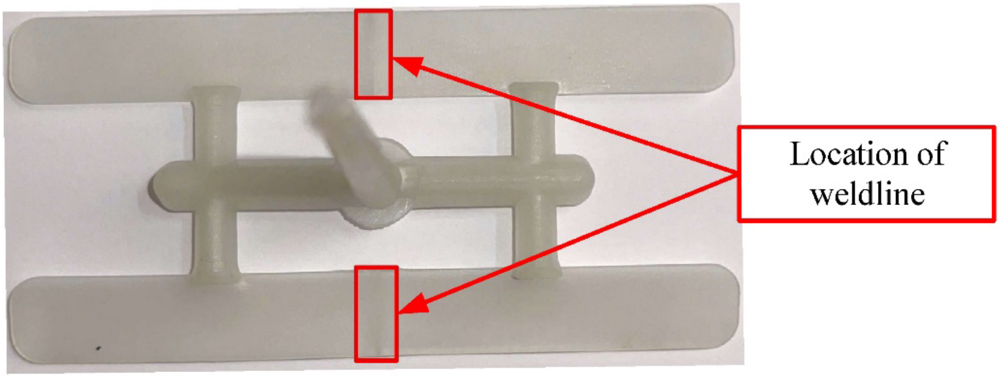


Figure 15. Weld-line location on a bending-test specimen [115].

When the material enters the cavity, it might become excessively chilled, impeding proper bonding. Excessive resin temperatures can lead to deterioration and gassing, preventing effective bonding. Additionally, undersized runners and gates can cause insufficient injection pressure. Weld lines introduce unpredictability to the performance of injection-molded components [116]. Table 10 summarises some of the found literature on the field regarding challenges on weld line.

Table 10. Studies carried out regarding weld line challenges.

References	Challenges	Highlights
Cao et al. [34]	Precise weld-line positioning in bi-injection molding	Introduces a two-time-dimensional model predictive control (MPC) strategy integrating conventional MPC with iterative learning control to regulate injection velocities of dual melt fronts, enabling accurate weld-line positioning and improved robustness against model mismatch in bi-injection molding processes.
Viljoen et al. [117]	Additive–weld-line interactions in filled composites	Validates that weld-lines in highly filled HDPE quaternary composites induce formulation-dependent shifts in deformation mechanisms, with DIC and SEM revealing altered localisation, stress-whitening, interlamellar slip, cavitation, and tensile-performance degradation.
Fukushima et al. [118]	Preventing weld-lines through mold design	Establishes that a low-cost sub-gate design can markedly shorten weld-lines by altering flow-front shape, promoting local melt mixing, and increasing meeting-point temperature, offering practical CAE-based guidelines for weld-line suppression.
Fereshteh-Saniee et al. [119]	Severe strength loss at weld-lines	Reveals that weld-lines in carbon-fibre sheet molding compounds induce pronounced local fibre alignment parallel to the defect and can reduce tensile strength by up to 80%, with automated eddy-current scanning successfully identifying failure-critical regions.
Jadhav and Gaval [120]	Predicting anisotropic weld-line strength accurately	Develops an integrative simulation framework that maps injection-molding outputs into structural analysis, capturing fibre orientation and weld-line characteristics to predict load–displacement response and failure location with accuracy exceeding 93%.

3.3.2. Sink-Mark

The Sink-mark is one of the most frequent flaws that may be observed on injection-molded components. Upon closing the pneumatic gates, a small depression form. This shrinkage in the gate region arises from lingering strains, and if the gates are not adequately sealed after the injection cycle, it can lead to potential failure of the component [121]. Figure 16 illustrates a schematic of a sink mark formation.

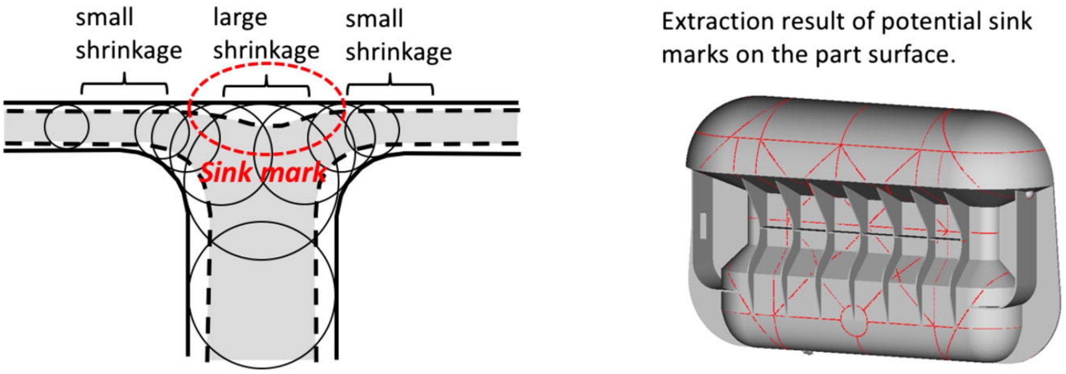


Figure 16. Schematic representation of sink-mark formation caused by non-uniform local shrinkage at a rib–wall intersection (**left**), and simulation-based extraction of potential sink-mark locations on the molded part surface (**right**) [122].

Hollow bubbles often present in the final product are typically observed in moldings, particularly those with a substantial wall thickness. The formation of sinks is primarily attributed to fluctuations in the cushion between cycles during operations. Furthermore, variations in injection pressure, reduced mold clamping, and alterations in cooling timing contribute to the emergence of sink marks in the ultimate molded products [123]. Table 11 summarises some of the found literature on the field regarding challenges on sink marks.

Table 11. Studies carried out regarding sink marks challenges.

References	Challenges	Highlights
Guo et al. [124]	Rib-induced sink-mark depth minimisation	Integrates DOE, finite-element simulation, and a genetic algorithm to identify the dominant effects of rib thickness, melt temperature, mold temperature, and coolant temperature, enabling robust optimization of sink-mark reduction in injection-molded thermoplastics.
Sun et al. [125]	Accurate prediction of sink-mark defects	Develops a two-step FEM-based procedure combining Moldflow boundary conditions with Abaqus PVT and viscoplastic subroutines, substantially improving quantitative prediction of sink-mark location and surface-profile evolution in injection-molded thermoplastics.
Inui et al. [122]	Early detection of potential sink-marks	Proposes a rapid CAD-based method that estimates local shrinkage from thickness distribution on finely tessellated solid models, automatically visualising potential sink-mark locations and supporting early-stage design refinement without time-intensive flow simulation.
Vanek et al. [126]	Non-uniform wall-thickness-induced sink defects	Demonstrates that sink marks and sink voids in thick-walled glass-fibre-reinforced PA66 components are governed chiefly by wall-thickness variation, thermal gradients, and incomplete core compensation; integrated Taguchi–CAE optimization markedly reduces defect susceptibility.
Wang et al. [127]	Non-uniform wall-thickness-induced sink defects	Demonstrates that sink marks and sink voids in thick-walled glass-fibre-reinforced PA66 components are governed chiefly by wall-thickness variation, thermal gradients, and incomplete core compensation; integrated Taguchi–CAE optimization markedly reduces defect susceptibility.

3.2.3. Short Shot

Short shot refers to the incomplete part produced during the IM process. Generally, if the mold cavity is not adequately filled due to any reason, it is termed as a short shot. This commonly occurs when a new part production cycle begins on the machine [128]. The material flow within the molds is a crucial factor influencing and causing short shots, as depicted in Figure 17. Material flow depends on various process parameters such as barrel temperature, injection pressure and injection timing [129]. Literature indicates that a low flow rate in low melting and molding temperature conditions can create air vents, leading to short-shot defects, as depicted in Table 12.

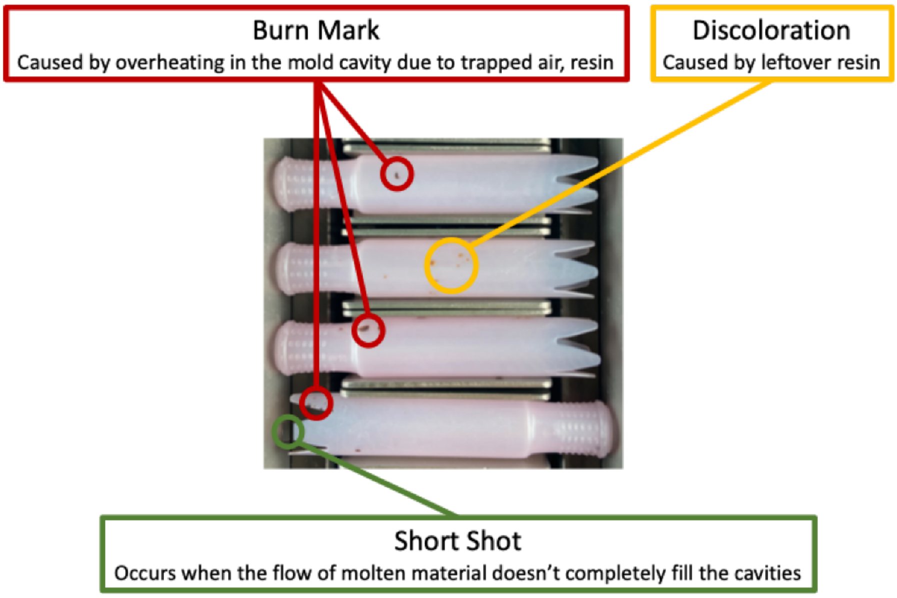


Figure 17. Short shot, burn mark and discoloration defects present on IM components [130].

Furthermore, short-shot defects may also be observed in molds with narrow or blocked gate openings. To address and eliminate this defect, increasing injection pressure and injection speed can result in complete molding. Additionally, raising the mold temperature significantly contributes to the reduction of short-shot defects [131].

Table 12. Studies carried out regarding short shot challenges.

References	Challenges	Highlights
Moayyedian et al. [132]	Preventing incomplete cavity filling defects	Demonstrates that short-shot susceptibility in thin-wall injection molding is governed primarily by melt temperature, filling time, and gate type; the combined simulation–Taguchi method enables reliable early prediction and process optimization before defect occurrence
Chen et al. [95]	Preventing short shots from mistimed switchover	Demonstrates that tie-bar elongation profiles can identify an appropriate filling-to-packing switchover without invasive cavity sensors, thereby helping to avoid short-shot defects and improve shot-to-shot consistency in injection molding.
L.D.Mahajan and P.N.Ulhe [133]	Short-shot reduction through parameter optimization	Taguchi–ANOVA analysis of CPVC elbow molding identifies mold-closing speed as the dominant parameter affecting short-shot susceptibility, with optimised injection pressure, mold pressure, and screw speed further improving filling completeness and part weight.
Liparoti et al. [116]	Short-shot formation at low mold temperatures	Demonstrates that, in micro-injection molding of isotactic polypropylene, short shots occur below 100 °C owing to premature solidification, whereas increasing mold temperature enables complete cavity filling and suppresses incomplete-shot formation.

3.2.4. Warpage

Warpage in IM occurs when the component, upon ejection from the mold, experiences deviation in its peripheral shape. This deviation is commonly known as warpage and can be attributed to several factors. These factors include ejecting the part when it is excessively hot, poor design of the ejection system, inadequate injection pressure or time, improper flow rates, and non-uniform cooling in the mold [134]. Figure 18 illustrates an IM component with warpage through FEA.

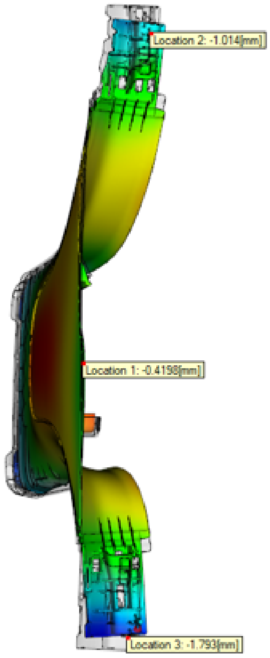


Figure 18. Warpage.

Warpage results from the development of undue stress in the IM process, leading to bends or twists in the final product geometry. The rapid cooling mechanism installed on molds to enhance productivity is a significant contributor to warpage defects. To mitigate such defects, it is crucial for the cooling channels to incorporate mechanisms that provide extended cooling periods, preventing premature cooling and minimizing warpage [131]. Table 13 summarises some of the found literature on the field regarding challenges on warpage.

Table 13. Studies carried out regarding warpage challenges.

References	Challenges	Highlights
Kitayama et al. [92]	Packing-induced warpage in molded parts	Shows that optimised variable packing-pressure profiles reduce differential shrinkage and significantly lower part warpage relative to constant-pressure packing, while simultaneously preserving shorter cycle times and improved dimensional accuracy
Carrupt and Piedade [135]	Mitigating cooling-induced part warpage variations	Reviews how mold-cavity materials, coatings, and especially conformal cooling-channel designs influence thermal uniformity, showing that more homogeneous heat extraction reduces differential shrinkage, shortens cooling time, and lowers warpage in injection-molded parts.
Chang et al. [136]	Maintaining uniform packing-induced density distribution	Develops a real-time PVT-based dynamic packing strategy that optimises packing timing and pressure across different part sections, equalises final specific volume, and improves shrinkage uniformity, warpage control, tensile strength, and production stability.
Parsons et al. [68]	Interfacial bonding, warpage, and fibre wash	Demonstrates that thermoplastic composite over-molding with discrete reinforcement inserts can enhance structural stiffness while maintaining rapid manufacturing cycles. The proposed waffle-type geometry mitigates warpage and fibre wash while improving stress transfer and manufacturability
Ren et al. [137]	Warpage control in over-molded assemblies	Demonstrates that warpage in ABS/PC over-molded components is governed predominantly by cooling time and material formulation; extended cooling and glass-fibre reinforcement markedly reduce deformation while improving dimensional stability and structural performance.
Laschet et al. [138]	Crystallisation-induced property gradients driving warpage	Demonstrates that warpage in semi-crystalline injection-molded parts is governed by locally varying crystallisation-dependent thermo-elastic properties; the multi-scale model predicts shrinkage and distortion more accurately than conventional constant-property approaches.

3.2.5. Burn Marks

Burn marks in plastic components are often observed, particularly when air becomes trapped in the mold cavity during the operation. This trapped air, subjected to high compression caused by injection pressure within the mold, leads to overheating of the material and manifests as burn marks on the final molding [131], as it is also seen in Figure 17. Additionally, burn marks may occur when the melting temperature is too high and there is excessive injection speed [139].

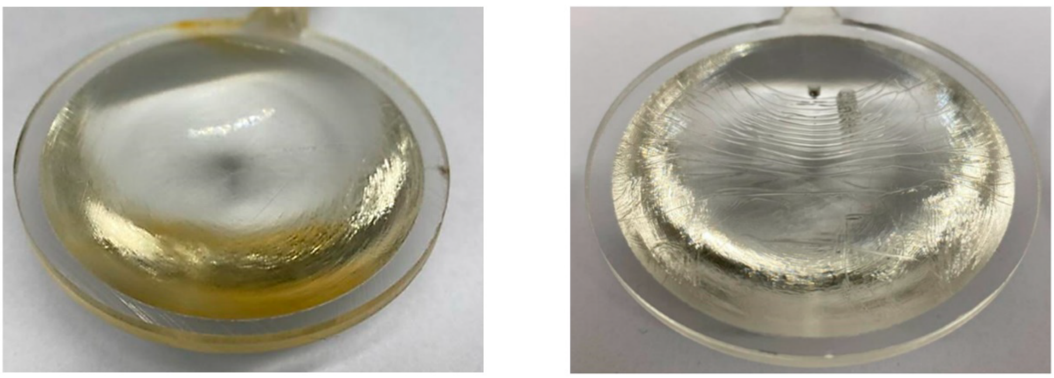
Preventive measures can be taken to eliminate burn marks in molded parts by adjusting key process parameters. Controlling the melting material temperature and the mold temperature is essential, as both parameters directly contribute to material overheating [139]. If the material becomes overheated, injecting it at a lower speed can help limit the risk of air entrapment during the injection process inside the mold, reducing the occurrence of burn marks [131]. Table 14 summarises some of the found literature on the field regarding challenges on burn marks challenges.

Table 14. Studies carried out regarding burn marks challenges.

References	Challenges	Highlights
Fukushima et al. [140]	Real-time detection of burn-mark onset	Demonstrates that low-cost gas sensors, particularly for carbon dioxide, can monitor gas-generation behavior during injection molding and provide a practical basis for online detection of burn-mark formation under critical filling conditions
Beheshtian Mesgaran et al. [141]	Trapped-air-induced burn marks in thin walls	Combines simulation, experimental verification, and mold redesign to identify burn-mark-prone thin-wall regions and eliminate the defect through targeted venting via ejector-pin placement, thereby improving surface quality and reducing corrective rework.
Tucker et al. [142]	Trapped-air-induced burn-mark and mold damage	Demonstrates that insufficient venting in micro-injection molding can generate extreme adiabatic heating and diesel-effect conditions, producing burn marks, polymer degradation, and potential tooling damage, thereby underscoring the necessity of dedicated venting design solutions.
Li et al. [143]	Trapped-air-induced surface burn marks	Demonstrates that external gas-assisted injection molding can eliminate severe surface burn marks without altering part or mold geometry; immediate gas injection is most effective, reducing quantified defect severity from 4.98% to 0%.
Araújo et al. [9]	Diagnosing burn marks from venting failure	Demonstrates that in-cavity pressure monitoring, supported by process simulation, can identify burn marks because of insufficient venting and trapped air, thereby enabling targeted process optimization and mold-maintenance interventions.

3.2.6. Flow Marks

Flow marks, which manifest as undesired patterns on molded components, can significantly impact the aesthetic appeal of the final product. These marks are indicative of non-uniformity in the flow pattern into the mold, particularly around the gate. Figure 19b demonstrates the flow marks on a polycarbonate piece.



(**a**) (**b**)

Figure 19. Images of test samples from the initial test series: (**a**) severe material yellowing; (**b**) noticeable flow marks on the surface [126].

https://doi.org/10.53941/jmem.2026.100027

When there is a temperature gradient in the melt, it leads to non-uniformity and may result in a slightly different color tone from the rest of the components. The main reported cause of flow marks is variations in the cooling speed of the material, particularly in components with varying wall thickness [144]. To eliminate flow marks, precautionary measures should be taken concerning injection time and pressure. It is crucial to ensure that the molding is filled before the cooling process begins. Making slight design changes, especially in straight (square-shaped) corners by molding round corners, is suggested to enhance the consistency of material flow inside the mold and reduce the occurrence of flow marks [131]. Table 15 summarises some of the found literature on the field regarding challenges on flow marks. Table 15 summarises some of the found literature on the field regarding challenges on flow marks.

Table 15. Studies carried out regarding flow marks challenges.

References	Challenges	Highlights
Vanek et al. [126]	Eliminating flow marks in thick lenses	Shows that, alongside sink-mark mitigation, optimised conventional injection-molding conditions for thick-walled polycarbonate lenses eliminated visible flow marks, indicating that appropriate gate design and carefully controlled thermal–pressure settings improve surface quality.
Gülçür et al. [145]	Unstable flow-front consistency during filling	Demonstrates that higher mold temperature improves melt-flow consistency and micro-feature replication in ultrasonic micro-injection molding, while image-based flow-front analysis provides a quantitative framework for assessing process stability and repeatability.
Mascher et al. [146]	Surface-structure effects on visible flow behavior	Demonstrates that EDM-generated mold-surface roughness can slightly increase flow path length in a material-dependent manner, although the effect remains secondary to melt temperature, mold temperature, injection pressure, and material viscosity.
Zhang et al. [147]	Chain-entanglement-driven flow-mark formation	Demonstrates that reducing molecular-chain entanglement in PP/polyolefin elastomer (POE)/talc composites lowers melt viscosity, delays unstable fountain flow, markedly suppresses flow-mark severity, and preserves tensile and impact performance, offering an industrially practical route to improved surface quality.
Zhang et al. [148]	Unstable fountain flow causing tiger stripes	Demonstrates that slight crosslinking of POE increases elastomer elasticity, stabilises fountain flow, delays unstable-flow onset, reduces gloss variation and stripe number, and markedly improves flow-mark resistance without sacrificing tensile processability.

3.2.7. Summary on the Outcome/Defects on Injection Mold Products

The production of defective items can have a significant impact on industrial performance, leading to resource wastage. Therefore, it is crucial to operate under optimal conditions. Existing literature on IM emphasizes the critical role of parameter selection and implementation. Parameters like material/mold heating, molten material plasticization, and moldings/molds cooling are considered subprocesses crucial for energy-efficient operations. Table 16 outlines defects and their causes associated with process parameters in IM [149–151]. Melt Temperature, Injection Pressure, and Injection Speed are identified as major contributors to defects such as short shots, weld lines, flow marks, burn marks, etc. Mold temperature and Cooling Time also play significant roles in contributing to specific defects. Holding Pressure and Holding Time are associated with one defect, namely Sink Marks. Table 16 further highlights the type of manipulation required during the molding process, whether it involves reduction or increment of certain parameters [131].

Table 16. Revealing the various defects caused by parameters [131].

Molding Defects	Melt (Material) Temperature	Mold Temperature	Holding Pressure	Cooling Time	Holding Time	Injection Pressure	Injection Speed
Weld-line	Increase			Moderate		Increase	Increase
Sink-mark			Increase	Increase	Increase		
Short shot	Increase					Increase	Increase
Warpage	Reduce	Reduce		Moderate			
Burn Marks	Reduce	Reduce				Moderate	Reduce
Flow Marks	Increase					Increase	Increase

Recent progress in various aspects of the IM process, as well as advancements in design and components, has prompted researchers to explore ways to improve the physical attributes of injection-molded parts. Optimized the IM parameters by employing the Taguchi-desirability function approach, which is used for virgin PP products, and reported higher factor setting for obtaining better warpage and cycle time [152].

According to Osarenmwinda and Olodu [153], they achieved minimal shrinkage by optimizing the IM parameters for High Density Polyethylene using the Taguchi method. Their findings revealed that cooling time emerged as the most influential factor, followed by refilling pressure, injection pressure, and injection temperature.

According to Ahmad et al. [154], they successfully minimized shrinkage by optimizing IM parameters for polypropylene molded components through the application of the Taguchi technique. Notably, they identified mold temperature as the most crucial element in achieving the desired outcome.

Numerous optimization research techniques have been employed to fine-tune the process parameters of IM for achieving products of acceptable quality. However, a challenge persists for researchers in practically implementing these optimizations due to various sources of variation during the process, leading to defects and resource wastage. Implementing artificial intelligence approaches in areas such as process monitoring and control, optimization of process parameters, mold design tailored to intricate product shapes, and the design of cooling channels that conform to the mold cavity shape could offer significant benefits by operating in the most optimal manner [7].

3.4. Machine Learning and AI Applications Relevant to MMIM

Before discussing the principal methods identified in the literature, it is important to distinguish more precisely between artificial intelligence, machine learning, and adjacent optimisation frameworks. In the present review, AI/ML is used in a narrower methodological sense to denote learning-based or rule-based computational approaches capable of extracting patterns, predictive relationships, or decision rules from data. This category includes methods such as artificial neural networks, radial basis function models when used as learning-based predictors, deep-learning architectures, and related predictive models. By contrast, conventional statistical and surrogate-based methods—including Taguchi design, design of experiments, response-surface methodology, and other low-order metamodels—are not treated here as AI in the strict sense. Rather, they are included as comparator methods and as part of the broader optimisation landscape against which the added value of AI/ML can be assessed. Likewise, simulation-based optimisation and deterministic control frameworks, including CAE-driven parameter studies and model-predictive control, are regarded as adjacent enabling approaches rather than as AI per se, unless they are directly coupled with learning-based or adaptive inference mechanisms.

A further category comprises evolutionary and computational-intelligence methods, such as genetic algorithms and fuzzy systems. These occupy an intermediate position: they are commonly associated with AI in the broad manufacturing literature, yet they are conceptually distinct from supervised machine learning because they do not primarily learn predictive mappings from data. Finally, hybrid intelligent frameworks combine elements from these different methodological families—for example ANN–GA, RSM–GA, simulation–AI, or sensor-integrated predictive-control systems—and are particularly relevant in MMIM because they allow prediction, optimisation, and control to be addressed simultaneously [155–157].

To facilitate a more precise analytical comparison, Table 17 distinguishes between AI/ML methods in the strict sense and adjacent statistical, surrogate-based, evolutionary, and control-oriented frameworks that are included in this review either as comparators or as components of hybrid intelligent systems relevant to MMIM.

The comparison in Table 17 indicates that no single methodological family can be regarded as universally superior across all MMIM contexts. Rather, different approaches exhibit distinct strengths and limitations depending on the nature of the process, the available data infrastructure, and the intended level of industrial deployment. Conventional surrogate-based methods such as RSM remain more transparent and experimentally efficient, and therefore retain value for bounded optimisation studies and preliminary parameter screening; however, they are less robust when MMIM behaviour is governed by strongly coupled nonlinear interactions and interfacial effects. ANN- and RBF-based models offer greater predictive power for nonlinear multivariate relationships, particularly in defect prediction and quality modelling, but their practical utility is constrained by data dependence, reduced interpretability, and limited transferability across materials, mold geometries, and machine platforms. Evolutionary methods are attractive for multi-objective search, yet their performance depends strongly on the fidelity of the objective model with which they are coupled. From an industrial perspective, the most promising direction appears to be hybrid and control-oriented frameworks integrating sensing, prediction, and adaptive correction, since these are more closely aligned with the real operational needs of MMIM. At present, however, these approaches remain less comprehensively validated under factory-scale conditions than their conceptual promise would suggest. This distinction is maintained throughout the remainder of the review in order to avoid conflating learning-based AI/ML methods with conventional optimisation or statistical modelling approaches.

Table 17. Comparative analytical synthesis of AI/ML methods and adjacent optimisation frameworks relevant to MMIM.

Method	Principal Advantages	Principal Limitations	Typical Areas of Application in MMIM
RSM	Computationally efficient; well suited to structured design-of-experiments data; highly interpretable; useful for identifying main effects and second-order interactions.	Limited ability to represent strongly nonlinear or high-dimensional process behaviour; performance deteriorates when complex thermo-rheological interactions dominate.	Parameter screening, process-window definition, warpage and shrinkage optimisation, preliminary multi-objective optimisation, and benchmark comparison with more advanced models.
ANN	Strong capability for capturing nonlinear multivariate relationships; effective for prediction of quality indices and defect occurrence; adaptable to data-rich environments.	Requires sufficiently large and representative datasets; reduced interpretability; susceptible to overfitting and limited extrapolation outside the training domain.	Defect prediction, quality prediction, virtual sensing, parameter–response mapping, and data-driven modelling of complex molding behaviour.
RBF models	Fast surrogate modelling; good interpolation accuracy for smooth nonlinear responses; lower training complexity than some deep neural architectures.	Sensitive to centre selection and data distribution; weaker extrapolative robustness; may lose accuracy under marked material or process variability.	Surrogate-based optimisation, warpage and shrinkage prediction, sequential approximation, and computationally efficient replacement of repeated simulation runs.
Genetic Algorithms (GA) and evolutionary optimisation	Strong global-search capability; suitable for multi-objective and constrained optimisation; useful when gradient information is unavailable or unreliable.	Computationally expensive; convergence may be slow; solution quality depends on encoding, parameter tuning, and objective-function formulation.	Process-parameter optimisation, gate and runner design, cooling-system optimisation, and multi-objective trade-offs between quality, cycle time, and material usage.
Hybrid models (e.g., RSM–GA, ANN–GA, RBF–PID, simulation–AI coupling)	Combines complementary strengths of prediction, optimisation, and control; often improves solution quality relative to single-method approaches; suitable for complex industrial decision-making.	Greater modelling and implementation complexity; higher tuning burden; transferability across machines, materials, and mold geometries remains limited.	Multi-objective optimisation, adaptive control, simulation-assisted decision support, and robust process tuning under variable material and operating conditions.

3.4.1. RSM Model

RSM, a metamodeling technique, commonly employs quadratic polynomials to depict the correlation between input and output variables. Despite its conventional nature, many researchers favour its widespread application due to its maturity and user-friendly attributes. The orthogonal array is frequently adopted as the design of experiment (DOE) methodology within this approach [158,159].

RSM, coupled with GA optimization algorithms, aims to minimize issues such as warpage, sink marks, or shrinkage. While various optimization techniques can be employed to address problems outlined in the RSM model, GA is often preferred by most authors for its perceived global optimization capability, preventing entrapment in local extremums. Some researchers explore the integration of RSM with gradient-based optimization techniques or utilize RSM to predict the impact of process parameters on the quality of molded parts [160–162]. Table 18 summarises some of the found literature on the field regarding the application of RSM to MMIM.

Table 18. Studies carried out on MMIM employing RSM.

References	Challenges	Highlights
Chen et al. [163]	RSM modeling of coupled molding responses	Applies second-order response surface methodology to construct predictive models for part length, warpage, and signal-to-noise behavior, enabling two-stage optimization of injection-molding parameters and markedly improving dimensional stability and process capability.
Li et al. [164]	RSM modeling of coupled quality responses	Establishes second-order response surface models linking fibre content, fibre aspect ratio, melt temperature, injection pressure, and cooling time to warpage, volumetric shrinkage, and residual stress, enabling robust multi-objective optimization of composite injection molding.
Ong et al. [165]	RSM-based rejection-rate minimisation in molding	Applies Box–Behnken response surface methodology to optimise melt temperature, mold temperature, and injection pressure for automotive ABS injection molding, establishing a significant quadratic model and reducing rejection rate to effectively zero under validated optimum conditions.
Kariminejad et al. [166]	Efficient RSM-based process optimization under constraints	Develops a central-composite-design response surface model linking mold temperature, cooling time, holding time, and barrel temperature to temperature differential and cycle time, enabling effective single- and multi-objective optimization of the injection molding process.
Zhao et al. [167]	Limited comparative deployment of RSM frameworks	Reviews response surface methodology as a practical surrogate-modeling approach for injection-molding optimization, particularly for correlating process variables with quality responses, while positioning it alongside ANNs, genetic algorithms, and Kriging-based methods.

3.4.3. RBF Model

The radial basis function (RBF) serves as a prevalent metamodel, although it is less frequently employed for optimizing process parameters compared to alternative models [168].

One prevalent learning algorithm for radial basis function networks involves initially selecting a set of data points as centres for the radial basis functions, followed by employing singular-value decomposition to determine the network weights [169]. Table 19 summarises some of the found literature on the field regarding the application of RBF model to MMIM.

Table 19. Studies carried out on MMIM employing RBF.

References	Challenges	Highlights
Heidari et al. [170]	Robust RBF modeling of coupled defects	Develops a radial basis function surrogate, validated through k-fold cross-validation, to model and optimise warpage and volumetric shrinkage in injection-molded UHMWPE hip liners, enabling accurate multi-objective process-parameter selection.
Chang et al. [171]	Accurate multi-objective RBF surrogate optimization	Employs radial basis function neural networks within a sequential approximation optimization framework to replace repeated finite-element reanalysis, enabling efficient parameter tuning and experimentally validated reductions in residual stress and volumetric shrinkage.
Lin et al. [172]	Limited RBF adaptability under material variability	Uses RBF-PID as a comparative baseline, showing that although it offers moderate accuracy and low computational burden, its adaptive performance declines under the uncertain rheological behavior of recycled-material injection molding.

3.4.4. Artificial Neural Network (ANN)

ANNs are mathematical models comprise individual processing units called neurons that resemble neural activity. Each processing unit sums weighted inputs and then applies a linear or nonlinear function to the resulting sum to determine the output [173]. The use of ANN replicates fundamental aspects of human brain functionality. This is gaining prominence due to the effectiveness of ANN as a robust tool for predicting highly nonlinear responses through function approximation. Numerous researchers have employed ANN as a predictive model to demonstrate the correlation between process parameters and quality indices [17]. In Figure 20 we can see a representation of a neural network predictor model that has Part Quality, Filling Time and Actual Injection Pressure as outputs and Melt Flow Rate, Injection Pressure and Mold and Melt Temperatures as inputs

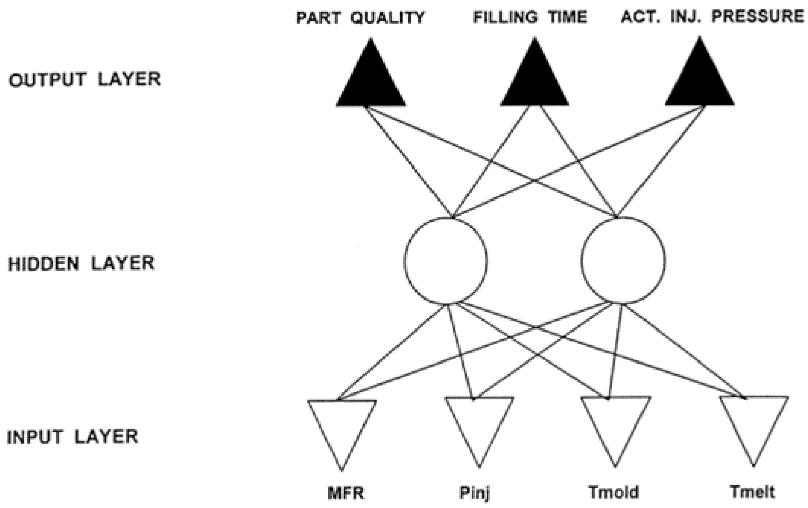


Figure 20. The architecture of neural network predictor model [173].

After studying the possibility of predicting the quality or soundness of the injected parts through an ANN model and based on the CAE software simulations the results showed the capability of the model developed in predicting the quality of injected parts in terms of lack or existence of short shot or weld line defect phenomenon [173]. Certain authors have asserted that the neural network predictor, utilizing learning data derived from CAE analysis, aligns closely with the outcomes observed in experimental studies [174–176]

Certain authors have asserted that the neural network model has the capability to precisely forecast product quality. This method is deemed a practical and effective tool for predicting quality criteria such as shrinkage, weight, or tensile strength [177–179].

The Artificial Neural Network (ANN) is acknowledged as a resilient model for anticipating the correlation between process parameters and the quality of molded components. Optimization of process parameters can be undertaken by relying on this approximate relationship [17]. Table 20 summarises some of the found literature on the field regarding the application of ANN to MMIM.

Table 20. Studies carried out on MMIM employing ANN.

References	Challenges	Highlights
Meyes et al. [180]	Bridging simulation–reality gaps in ANN prediction	Applies a deep artificial neural network with simulation-based pre-training and experimental fine-tuning to injection molding, improving prediction accuracy, stability, and learning efficiency for part weight and dimensional-quality estimation.
Moayyedian et al. [181]	Weighted ANN optimization of multiple defects	Applies a Levenberg–Marquardt backpropagation ANN to optimise injection-molding parameters for a thin-walled polypropylene part, predicting a lower combined defect index than Taguchi and achieving close simulation agreement with only 1.5% error.
Moayyedian et al. [182]	Accurate ANN modeling of coupled defects	Applies ANN-based soft computing, particularly multilayer perceptron models, to predict shrinkage and warpage in dashboard injection molding from four process parameters, enabling subsequent multi-objective optimization of defect reduction.
Zhao et al. [167]	Reliable ANN-based nonlinear quality prediction	Reviews artificial neural networks as a prominent intelligent modeling approach for injection molding, highlighting their capacity to capture nonlinear relationships between process parameters and molded-part quality while reducing dependence on trial-and-error optimization.
[183]	Accurate ANN prediction of demolding force	Develops and validates an ANN-based model for effective demolding-force prediction in polycarbonate injection molding, with the scaled conjugate gradient algorithm delivering the highest accuracy and identifying packing pressure as the dominant parameter.

3.4.4. Statistical Learning-Driven Modified Simplex Method

The Statistical Learning-Driven Modified Simplex Method is an optimization framework that integrates the classical simplex search strategy with statistical learning principles to improve search efficiency, robustness, and adaptability in complex design spaces. Rather than relying solely on geometric transformations of the simplex, the method exploits patterns identified from previously evaluated solutions to guide the exploration towards more promising regions. This data-informed mechanism enables a more effective balance between exploration and exploitation, particularly when objective functions are nonlinear, noisy, or computationally expensive. By incorporating predictive insight into the iterative update process, the approach enhances convergence behavior, reduces unnecessary evaluations, and provides a basis for intelligent optimization in engineering and manufacturing applications. Luangpaiboon et al. [184] conducted a data-driven optimization study in which the Statistical Learning-Driven Modified Simplex Method improved dimensional consistency, reduced response variability, and lowered experimental effort through statistically guided simplex-based parameter refinement in injection molding.

4. Discussion

Beyond compiling examples of AI use in injection molding, the present review makes a broader scientific contribution by clarifying how artificial intelligence intersects with the distinctive physical and operational challenges of MMIM. A central implication of this review is that not all insights derived from conventional injection molding can be transferred directly to MMIM without qualification. In particular, the analysis shows that the relevance of AI in this domain does not arise merely from general advances in machine learning, but from the exceptional sensitivity of MMIM to coupled thermal, rheological, geometric, and interfacial phenomena. The review therefore contributes a structured interpretation of the field by linking process physics, defect mechanisms, modelling strategies, and implementation constraints within a single analytical framework. This integrative perspective constitutes a key novelty of the study, as it allows AI methods to be assessed not only in terms of predictive accuracy, but also in relation to manufacturability, robustness, interpretability, and industrial deployment potential.

A more discriminating comparison of the reviewed methods suggests that the key issue is not simply whether AI outperforms conventional optimisation, but under what conditions different methodological families become preferable. Interpretable statistical and surrogate-based approaches remain advantageous when the design space is relatively bounded and the need for experimental transparency is high. By contrast, machine-learning models become more attractive when process–response relationships are strongly nonlinear and rich sensor or production data are available. Evolutionary and hybrid methods are particularly useful in multi-objective settings, especially when defect mitigation, cycle time, and dimensional stability must be balanced simultaneously. Nevertheless, the literature also shows that predictive accuracy alone is an insufficient criterion for methodological superiority: models intended for MMIM must also be judged in terms of transferability, validation depth, robustness to industrial variability, and their capacity to support actionable decision-making in real manufacturing environments.

Nevertheless, a critical reading of the literature indicates that enthusiasm surrounding AI in MMIM must be balanced against the realities of process complexity and industrial implementation. MMIM is not simply a more advanced version of single-material injection molding; it is a manufacturing environment characterised by strongly coupled thermal, rheological, geometric, and interfacial phenomena. The combination of dissimilar materials introduces additional uncertainty in relation to compatibility, bonding integrity, differential shrinkage, and local defect susceptibility. In such circumstances, conventional empirical optimization is often inadequate, yet AI models trained on limited or poorly structured datasets may also fail to generalise reliably under industrial variability.

Three implications emerge particularly clearly from the review.

- First, AI appears especially promising in areas where MMIM generates large volumes of multivariate data, but where causal relationships remain difficult to formalise analytically. This includes material selection, adaptive blending, in-mold sensing, defect prediction, and process-window optimization. The manuscript correctly argues that data-driven systems may support more intelligent decisions regarding material combinations, sustainability constraints, and quality requirements.
- Second, the most valuable role of AI is likely to lie in predictive process control rather than isolated offline optimization. Real-time monitoring, defect recognition, and dynamic parameter correction are repeatedly identified in the manuscript as high-value applications because they respond directly to one of the principal weaknesses of MMIM: sensitivity to small process disturbances. The prospect of closed-loop systems combining machine learning, sensor feedback, and intelligent adjustment is therefore particularly compelling.

- Third, the review also makes clear that broader adoption remains constrained by non-technical barriers. These include data security, the need for specialised expertise, implementation cost, model transparency, and trust in algorithmic decision-making. Such factors are not secondary; they are central to industrial acceptance.

Accordingly, the present discussion suggests that future progress in AI-assisted MMIM will depend on more than the development of increasingly sophisticated algorithms. It will require:

- better-quality and more standardised industrial datasets;
- stronger integration between material science, process engineering, and AI modeling;
- greater emphasis on interpretable and explainable systems;
- and validation under real factory conditions rather than solely under controlled laboratory environments.

Overall, the literature supports the view that AI can make a substantial contribution to MMIM, particularly in improving adaptability, predictive capability, and defect prevention. However, the field has not yet reached the stage at which AI can be regarded as a universally mature or fully transferable solution. Its real value will depend on whether future research can bridge the current gap between promising computational demonstrations and robust, scalable industrial implementation.

From this perspective, the principal novelty of the present review is conceptual as much as topical. Rather than treating AI-assisted MMIM as a collection of isolated algorithmic case studies, the review demonstrates that meaningful progress depends on the coordinated development of datasets, process knowledge, sensing infrastructure, validation protocols, and control logic. The field's central challenge is therefore not simply algorithm selection, but the integration of AI within a technically credible and industrially actionable manufacturing framework.

5. Conclusions

This review has examined the emerging role of artificial intelligence within multimaterial injection molding through a systematic and critically structured analysis of the literature. The evidence reviewed suggests that AI may make a meaningful contribution to MMIM, particularly in defect prediction, process monitoring, parameter optimisation, and adaptive control. However, the present knowledge base remains uneven in methodological maturity, validation depth, and industrial transferability, and many of the reported advances are still derived from laboratory-scale, simulation-assisted, or otherwise bounded case studies. Accordingly, the conclusions drawn here identify the most credible directions of development rather than demonstrating the universal readiness of AI for industrial MMIM deployment. Collectively, they reflect the current state of knowledge regarding the integration of AI within MMIM, while also highlighting the principal technological opportunities, methodological constraints, and strategic directions for future academic and industrial development:

- MMIM has established itself as a strategically important manufacturing route for producing polymer components with integrated and multifunctional properties; however, its industrial deployment remains constrained by process complexity, material–interface interactions, and the strong coupling between thermal, rheological, and geometric variables.
- The reviewed literature suggests that artificial intelligence can support MMIM in areas such as defect prediction, process monitoring, and parameter optimisation, particularly where conventional empirical or statistical approaches struggle to capture nonlinear process behaviour.
- Reported improvements in dimensional accuracy, process stability, and defect mitigation are encouraging, but they are not yet sufficiently consistent across materials, machine platforms, and production environments to justify strong claims of broad industrial transferability.
- The integration of AI with in-mold sensing, process simulation, and closed-loop control appears to be one of the most promising research directions for MMIM; nevertheless, evidence for robust factory-scale implementation remains limited.
- Significant barriers remain, including restricted access to high-quality industrial datasets, insufficient cross-material and cross-machine generalisability, lack of standardised benchmarking procedures, and the practical difficulty of embedding AI tools within existing production infrastructures.
- AI should therefore be regarded, at the present stage of development, as an emerging enabling framework for MMIM rather than as a universally mature or fully validated industrial solution. Its longer-term value will depend on stronger validation, improved data infrastructures, more interpretable models, and closer integration with real manufacturing workflows.

In this sense, the novelty of the present article lies in offering a synthesis that is simultaneously technological, methodological, and strategic. It not only reviews existing AI applications in IM and MMIM, but also identifies the principal conditions under which such approaches are likely to become genuinely transformative: the availability of high-quality and standardised datasets, closer integration between process engineering and data science, greater emphasis on interpretable and transferable models, and validation under realistic industrial conditions. The review therefore contributes both a critical map of the current state of the field and a research agenda for the next stage of AI-assisted MMIM development. Across the reviewed methodological families, the evidence suggests that interpretable statistical surrogates remain the most transparent, learning-based models the most expressive for nonlinear prediction, and hybrid sensor-integrated control frameworks the most industrially relevant, although the latter still suffer from comparatively limited large-scale validation.

6. Future Directions

Future work in AI-assisted MMIM should focus on three priorities. First, the field requires larger, better-structured, and more standardised datasets capable of supporting robust model development across different material combinations, mold geometries, and machine platforms. Second, greater emphasis should be placed on interpretable and hybrid frameworks that combine sensing, simulation, and adaptive control rather than relying solely on isolated predictive models. Third, the literature would be strengthened by more extensive validation under realistic industrial conditions, particularly in relation to cross-material generalisability, closed-loop process stability, and the practical integration of AI tools within existing manufacturing infrastructures. Progress in these areas is likely to determine whether AI evolves from a promising analytical aid into a reliable industrial capability for MMIM.

Author Contributions

Conceptualisation: A.F.V.P. and R.J.D.A.; methodology: P.J.S.; validation: R.J.D.A.; formal analysis: P.S. and F.S.; investigation: P.S. and F.S.; data curation: A.F.V.P.; writing—original draft preparation: P.S., F.S. and A.F.V.P.; writing—review and editing: A.F.V.P.; visualisation: P.J.S.; supervision: R.J.D.A.; project administration: R.J.D.A.; funding acquisition: R.J.D.A. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

During the preparation of this work, the author(s) used Grammarly Premium v6.8.263 to verify and improve the British (UK English) language employed. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

Appendix A

PRISMA 2020 flow diagram for new systematic reviews, which included searches of databases and registers.

This appendix provides the detailed PRISMA 2020 flow diagram describing the study identification, screening, eligibility assessment, and inclusion process undertaken in this systematic review. The diagram ensures transparency and reproducibility of the literature selection methodology in accordance with the PRISMA 2020 statement.

The systematic search strategy was conducted across multiple scientific databases and relevant registers to identify peer-reviewed literature related to MMAM. The search combined predefined keywords associated with multimaterial processing, interface behavior, graded materials, and additive manufacturing technologies. Boolean operators and controlled vocabulary terms were applied where appropriate to maximise sensitivity and specificity. The selection process is depicted in the flowchart of Figure A1.

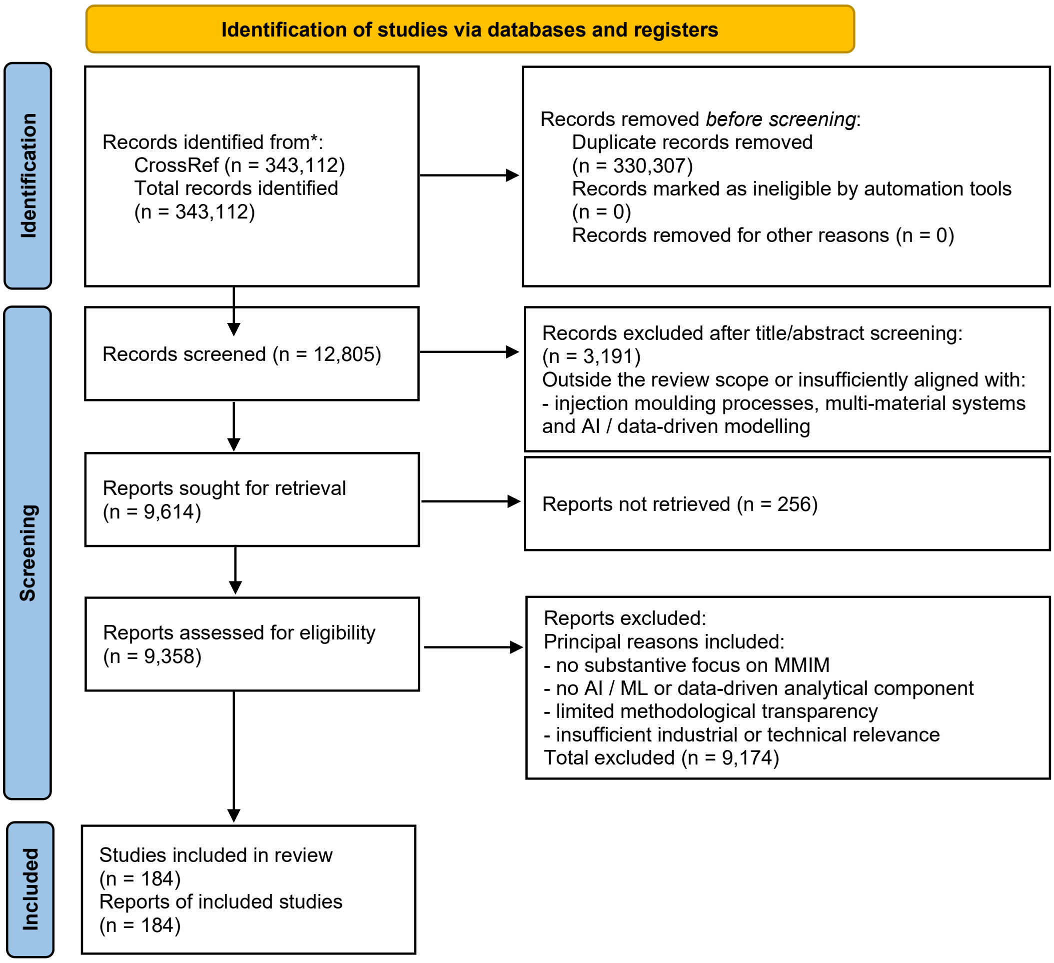

Figure A1. PRISMA2020 flowchart for the MMIM study.

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