

MULTI-ATTRIBUTE RISK PRIORITIZATION OF INJECTION-MOULDING DEFECTS USING DMAIC, FMEA, MAFMA AND FUZZY AHP

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ABSTRACT

This study investigates how failure-prioritisation decisions change when conventional Failure Mode and Effects Analysis (FMEA) is extended with Multi-Attribute Failure Mode Analysis (MAFMA) and fuzzy Analytic Hierarchy Process (FAHP) within a DMAIC quality-improvement framework. The industrial case concerns an automotive injection-moulding process that produced 85,016 units, of which 5,131 were defective (6.04%); short shot accounted for 51.4% of recorded defects. Conventional FMEA ranked operator/SOP-related failure first (RPN 100), whereas MAFMA-FAHP ranked inadequate mould design first (priority 0.47). Independent AHP checks confirmed acceptable consistency for the criterion and expected-cost pairwise matrices ($CR=0.070$ and 0.089). Sensitivity analysis showed that mould design remained the top-ranked cause under equal weights, $\pm 20\%$ changes in expected-cost weight, and a no-cost scenario. The findings show that explicit weighting and economic consequence can materially alter improvement priorities and that robustness checks should accompany multi-attribute risk ranking.

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1. INTRODUCTION

Quality losses in injection moulding are rarely attributable to a single mechanism. Product geometry, mould condition, processing parameters, material condition, and operator actions interact throughout filling, packing, cooling, and ejection. A short shot, for example, is observed as incomplete cavity filling, but the initiating mechanism may be insufficient flow, restriction in the mould, inadequate venting or cooling, material variation, unstable machine settings, or a mechanical problem that indirectly disturbs cavity filling. This multi-causal structure makes defect reduction a prioritisation problem as much as a technical troubleshooting problem. An organization must decide not only which defect

occurs most frequently, but also which underlying cause should receive scarce engineering attention and improvement expenditure.

Six Sigma provides a structured route for converting defect data into improvement decisions. The Define-Measure-Analyze-Improve-Control (DMAIC) cycle is widely used to define critical quality characteristics, quantify baseline performance, identify causes, select improvement actions, and establish controls. Manufacturing reviews show that systematic use of DMAIC is associated with defect reduction, productivity improvement, and higher process capability (Purba et al., 2021). Within injection moulding, this architecture is particularly relevant because defects such as short shot, flash, sink mark, flow mark, and contamination can

emerge from interacting process and tooling conditions. Industrial evidence also shows that Six Sigma can support yield improvement in plastic injection moulding when defect data and process parameters are analysed systematically (Hsiao et al., 2023; Shankaranarayana, 2017).

A recurring difficulty appears in the Analyze and Improve phases. Failure mode and effects analysis (FMEA) is often used to prioritize causes through the risk priority number (RPN), calculated from severity (S), occurrence (O), and detection (D). FMEA is attractive because it is transparent, practical, and compatible with cross-functional industrial problem solving. However, conventional RPN has well-documented limitations: different S-O-D combinations can yield identical values, the three dimensions are implicitly treated as equally important, ordinal ratings are multiplied as though they were ratio-scaled, and economic consequences are not explicitly represented. These limitations continue to motivate integration of FMEA with fuzzy logic and multi-attribute decision-making (MADM) methods (Aleksić et al., 2025; Huang et al., 2020; Liu et al., 2013). Recent hybrid models similarly show that weighting and uncertainty treatment can materially change risk rankings (Chakhrit et al., 2024; Shakibaei et al., 2024).

Multi-Attribute Failure Mode Analysis (MAFMA), introduced by Braglia (2000), offers a conceptually useful extension because it treats failure prioritisation as a multi-attribute decision problem and adds expected cost to severity, occurrence, and detectability. Expected cost is particularly meaningful when an infrequent but structurally consequential failure triggers tooling repair, downtime, rework, or prolonged production disruption. Fuzzy AHP further permits relative criterion importance to be expressed through pairwise judgments and triangular fuzzy numbers rather than relying on one unweighted multiplicative RPN. Contemporary studies combining FMEA and fuzzy AHP in manufacturing likewise emphasize that unequal risk-factor importance and uncertain expert judgments should be represented explicitly rather than hidden within a single RPN (Perić et al., 2025).

The present study examines this decision problem in the production of an automotive pipe throttle-grip component manufactured from polyoxymethylene by injection moulding. Injection moulding is particularly appropriate for this question because defect generation can originate from interacting material, process, tooling, and operator conditions. Recent injection-moulding studies show that DMAIC and related data-driven approaches can identify process parameters and mould-related factors that materially affect defect rates (Hsiao et al., 2023; Köken et al., 2026; Ratsaree & Chotiprayanakul, 2026). However, identifying plausible causes and deciding which cause deserves scarce improvement resources are not the same analytical task. Accordingly, this paper asks three questions. First, how does the ranking of injection-moulding failure causes change when conventional FMEA is extended with weighted severity, occurrence, detection, and expected

cost? Second, is the resulting FAHP-based ranking internally consistent and arithmetically reproducible? Third, is the preferred improvement priority robust to plausible changes in criterion weighting? The contribution is therefore not a claim that MAFMA-FAHP is universally superior to FMEA, but an empirically traceable demonstration of when and why a multi-attribute model can change an industrial improvement decision.

2. LITERATURE REVIEW

2.1 DMAIC and defect-oriented process improvement

DMAIC structures improvement as a sequence of linked decisions. Define establishes the process boundary, customers, outputs, and critical-to-quality (CTQ) characteristics. Measure quantifies baseline performance and process stability. Analyze identifies plausible causal mechanisms. Improve selects and develops countermeasures. Control seeks to sustain the improved condition. The value of the architecture is that a proposed improvement should be traceable backward to a measured performance gap and a diagnosed cause, rather than being selected through intuition alone. In this study, the sequence is operationalized through SIPOC and Pareto analysis in Define, a p-chart and sigma metrics in Measure, fishbone analysis and FMEA in Analyze, and MAFMA-FAHP in Improve.

The sigma metric is used here as a descriptive capability indicator rather than as a claim that the underlying defect-generation process follows an idealized Six Sigma distribution. For attribute data, defects per unit (DPU), defects per opportunity (DPO), and defects per million opportunities (DPMO) provide an interpretable baseline. The p-chart complements these metrics by testing whether weekly defect proportions are statistically stable. This distinction matters because a high or low sigma estimate alone does not identify whether variation is common-cause or associated with special conditions.

2.2 Conventional FMEA and its prioritisation problem

In process FMEA, each potential cause is scored for severity, occurrence, and detection. The conventional RPN is $RPN = S \times O \times D$. The method is useful for structured discussion but its arithmetic creates ambiguity. Equal RPNs may represent different risk profiles, and equal weights are imposed implicitly. Liu et al. (2013) documented these weaknesses across the FMEA literature, while Huang et al. (2020) showed that the continued development of improved FMEA models is largely driven by shortcomings in risk ranking and uncertainty treatment. These critiques do not make conventional FMEA unusable; rather, they suggest that RPN should be interpreted as one decision aid, especially when competing causes have different cost implications.

For industrial improvement, cost is not synonymous with severity. Severity expresses the consequence of a failure to product, process, or customer, whereas expected cost may capture the resources required to correct the failure or the economic burden if it persists. A mould-design problem can therefore merit higher intervention priority than an operator-related problem even when its conventional RPN is lower, if the design issue causes expensive repair, component breakage, line interruption, or recurrent defect generation.

2.3 MAFMA and fuzzy AHP

MAFMA reframes failure-cause selection as a hierarchical multi-attribute problem. The goal is to select the most critical cause; the criteria are severity, occurrence, detectability, and expected cost; and the alternatives are the identified causes. Braglia (2000) proposed this logic to integrate heterogeneous information into a more complete criticality analysis. In the present application, FAHP is used to derive criterion weights and the local expected-cost priorities. Severity, occurrence, and detection local priorities are normalized from FMEA ratings, while the expected-cost priorities are derived from pairwise judgments.

Fuzzy AHP is appropriate when experts can state relative preference more confidently than precise cardinal values. Pairwise AHP judgments are translated to triangular fuzzy numbers (TFNs), processed to derive relative weights, and then checked against the underlying crisp pairwise matrices for consistency. This does not eliminate subjectivity; rather, it makes expert preference explicit and auditable. Recent FMEA-MADM literature reinforces this point: fuzzy and multi-criteria extensions are useful primarily because they represent unequal criterion importance and judgment uncertainty more transparently than conventional RPN (Aleksić et al., 2025; Chakhrit et al., 2024).

2.4 Decision logic and analytical propositions

The integrated framework rests on a simple decision-theoretic distinction between frequency-based importance and resource-sensitive importance. Pareto analysis identifies where defects are concentrated, FMEA identifies which causal mechanisms appear risky under severity-occurrence-detection ratings, and MAFMA asks whether those causes remain priorities when the organization explicitly values criteria differently and considers economic consequence. The three layers are complementary rather than substitutes. A frequent defect may not originate from the most expensive cause, and the highest RPN cause may not justify the largest engineering investment. For this reason, the framework separates defect selection from cause selection and then separates cause screening from investment prioritisation.

Three analytical propositions guide interpretation. Proposition 1 is that unequal criterion weights can change the rank order produced by unweighted RPN. Proposition

2 is that adding expected cost can amplify a technically important cause whose economic consequence is not represented by conventional RPN. Proposition 3 is that a decision should not be regarded as robust merely because one weighting scheme produces a clear first rank; the preferred cause should remain stable under plausible perturbations of criterion weights. These propositions motivate both the FMEA-versus-MAFMA comparison and the sensitivity analysis reported later.

This interpretation is particularly important in small-sample expert assessments. FAHP can formalize linguistic preference and soften crisp comparisons, but it does not eliminate dependence on expert knowledge. The model should therefore be used as a structured deliberation tool. Consistency analysis verifies logical coherence, while sensitivity analysis and cross-functional review address robustness. In the present case, the independent CR checks demonstrate that the original judgments are internally acceptable, but a future multi-expert design would provide stronger evidence through aggregated pairwise matrices and inter-rater analysis.

A further implication concerns the distinction between diagnosis and decision. Root-cause analysis attempts to explain why a defect occurs, whereas prioritisation attempts to decide where limited improvement resources should be committed. These are related but not identical tasks. A cause may be technically plausible yet low priority because it is rare, inexpensive, or easily detected. Conversely, a cause may deserve early intervention even when its conventional RPN is not maximal if it creates expensive recurrent failures or requires a design change with a long lead time. Keeping these tasks separate reduces the temptation to equate the largest Pareto bar, the highest RPN, and the best investment target. In an industrial setting, those three answers can legitimately differ. The integrated DMAIC-MAFMA logic used here makes the transitions explicit: Pareto selects the defect family, fishbone and FMEA structure causal evidence, and MAFMA-FAHP converts that evidence into a weighted improvement decision. This layered interpretation also improves auditability because managers can trace a final priority back to the individual ratings and weights that generated it. If stakeholders disagree with the result, they can challenge a specific assumption rather than rejecting the entire analysis.

For publication-oriented case research, this traceability is also a methodological advantage. Industrial studies are often criticized because the final recommendation appears to emerge from a sequence of familiar quality tools without demonstrating why one action was selected over another. By retaining the intermediate rankings, criterion weights, and global contributions, the present framework allows a reviewer to reconstruct the decision. It also prevents overclaiming: the model supports selection of an improvement target, but it does not by itself demonstrate that the selected action will reduce defects after implementation. That distinction is especially important when the recommended intervention is a mould redesign, because performance can only be established through subsequent trial and

production data. The analytical contribution is therefore the transparent prioritisation mechanism and the documented change in decision logic, while engineering effectiveness remains a separate empirical question. This separation keeps the manuscript analytically defensible and aligned with the evidence actually available from the industrial case.

3. METHODOLOGY

3.1 Industrial case and data

The case concerns a two-wheeler automotive component produced by an Indonesian injection-moulding manufacturer. To preserve industrial confidentiality in the journal manuscript, the company is referred to as the case manufacturer. The product is a pipe throttle-grip component manufactured from POM Duracon GH20. Historical production and quality data covered August 2023 to January 2024. The available dataset included weekly output, defective quantity, defect type, process observations, interviews with production personnel, and expert pairwise judgments used in the MAFMA-FAHP stage.

Across the six-month observation horizon (August 2023–January 2024), production records contained 85,016 units, of which 5,131 were recorded as defective, giving a directly verifiable defective-unit proportion of 6.04%.

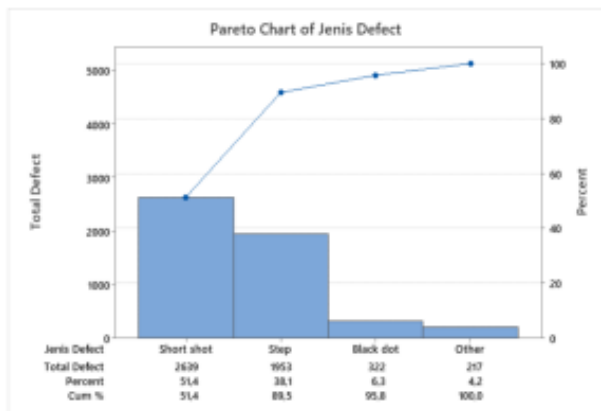


Figure 1. Distribution of recorded defect types

The company internal target was a maximum defect proportion of 2%. Pareto analysis of recorded defect categories identified short shot as the dominant category, representing 51.4% (2,639 units), followed by step (38.1%), black dot (6.3%), and other defects (4.2%) (Figure 1). These directly traceable production counts were used for baseline characterization in the present manuscript.

3.2 DMAIC analytical sequence

The analytical sequence was designed to preserve traceability from observed defects to prioritized causes. In Define, a SIPOC representation bounded the production process from material loading to the release of the moulded component, while Pareto analysis

identified the dominant defect. In Measure, three CTQs (short shot, step, and black dot) were used to calculate DPO, DPMO, and sigma level. A p-chart was used as a diagnostic assessment of weekly defect-proportion stability. In analyze, a cause-and-effect analysis for short shot was developed from direct observation and interviews with production leaders and quality-control personnel. Four actionable causes were subsequently evaluated using FMEA. In Improve, the same four causes became alternatives in the MAFMA hierarchy, with severity, occurrence, detection, and expected cost as decision criteria.

3.3 Baseline quality metrics

Baseline quality performance was summarized using directly verifiable production counts and defect proportions (Table 1). The overall defective-unit proportion was calculated as defective units divided by total production. Pareto shares were calculated from the recorded defect-category counts. Because the scientific contribution of this paper concerns failure-cause prioritisation rather than process-capability estimation, DPMO and sigma conversion were not used as inferential evidence.

Table 1. Reproducible baseline quality summary

Metric	Value
Total production	85,016 units
Defective units	5,131 units
Defective-unit proportion	6.04%
Dominant defect	Short shot: 51.4% (2,639 units)

This choice also avoids conflating a unit-level defective count with a defect-opportunity model when individual units may contain multiple potential quality opportunities.

3.4 FMEA and MAFMA-FAHP construction

The fishbone analysis identified four actionable causes for the dominant short-shot failure mode: C1, operator does not adequately understand or follow the SOP; C2, damaged G1/4 thread in the cooling-pipe connection; C3, inadequate mould design associated with repeated insert pin-shaft problems; and C4, contamination with recycled material. FMEA assigned S, O, and D ratings using the plant's assessment scales (Table 2).

Table 2. Conventional FMEA ratings for short-shot causes

Cause	S	O	D	RPN	Rank
C1 Operator/SOP	5	4	5	100	1
C2 Cooling thread damage	5	3	4	60	3=
C3 Inadequate mould design	5	5	3	75	2
C4 Recycled-material contamination	5	3	4	60	3=

The resulting RPN values were 100, 60, 75, and 60, respectively. Thus, conventional FMEA selected C1 as the first intervention priority.

For MAFMA, the four risk attributes were treated as criteria and the four causes as alternatives. Pairwise comparison of the criteria was obtained from a production foreman. The fuzzy-synthesis procedure in the original study produced criterion weights of 0.23 for severity, 0.27 for occurrence, 0.08 for detection, and 0.43 for expected cost (Table 3). Expected cost therefore accounted for the largest share of the decision weight.

Table 3. MAFMA criterion weights and local expected-cost priorities

Criterion	Weight
Severity	0.23
Occurrence	0.27
Detection	0.08
Expected cost	0.43

Table 4. Expected-cost local priorities for failure causes

Cause	Expected-cost local priority
C1 Operator/SOP	0.12
C2 Cooling thread damage	0.11
C3 Inadequate mould design	0.70
C4 Recycled-material contamination	0.08

A second pairwise matrix compared C1-C4 from an expected-cost perspective and yielded local priorities of 0.12, 0.11, 0.70, and 0.08, respectively (Table 4).

3.5 Independent consistency and arithmetic checks

Before interpreting the FAHP results, the original crisp pairwise matrices were independently re-evaluated using the standard AHP principal-eigenvalue consistency procedure. For the four criteria, the reconstructed matrix produced $CR=0.070$; for the expected-cost alternatives, $CR=0.089$. Both are below the commonly used 0.10 threshold. This independent check replaces the negative CR values reported in the student thesis, which arose from an incorrect calculation of the maximum eigenvalue and consistency index. The correction does not alter the elicited pairwise judgments or the resulting priority direction; it only restores the mathematical validity of the consistency test.

A second quality-control check concerned the final MAFMA ranking. The total-priority values are additive weighted scores (the sum of global priorities across the four criteria). The original table assigned rank labels 4 and 3 to scores 0.17 and 0.16, respectively, which is arithmetically reversed. In this manuscript, ranks are assigned directly from descending total-priority values: 0.47, 0.20, 0.17, and 0.16. These corrections do not change the primary conclusion that C3 is the dominant MAFMA priority.

4. RESULTS AND DISCUSSIONS

4.1 Baseline quality performance

The production records show a defective-unit proportion of 6.04% (5,131 of 85,016 units), approximately three times the company's internal 2% target. Short shot was the dominant recorded defect category, accounting for 51.4% (2,639 units), followed by step (38.1%), black dot (6.3%), and other defects (4.2%). The Pareto result therefore justified focusing the subsequent cause analysis on short shot rather than distributing improvement effort equally across all recorded defect categories.

The fishbone analysis suggested that short shot was not exclusively a machine-parameter problem. Causes spanned human, machine/tooling, and material domains. The four causes taken forward to FMEA were deliberately actionable: operator understanding of SOP, damaged cooling-thread condition, inadequate mould design, and recycled-material contamination. This set is important because it creates a realistic prioritisation conflict. Corrective action for C1 could involve training and supervision, whereas C3 could require engineering redesign and tooling expenditure.

4.2 Priority reversal between FMEA and MAFMA

Conventional FMEA ranked C1 first with RPN 100, followed by C3 with RPN 75. C2 and C4 were tied at RPN 60. The ranking therefore suggested that the immediate improvement emphasis should be placed on operator comprehension and adherence to the standard operating procedure (Figure 2).

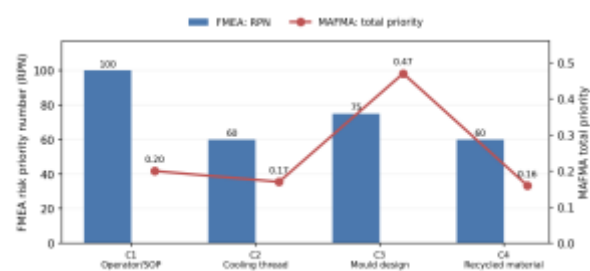


Figure 2. Comparison of conventional FMEA and MAFMA prioritisation

MAFMA produced a different decision. C3 obtained a total priority of 0.47, more than twice the score of C1 (0.20), followed by C2 (0.17) and C4 (0.16).

4.3. Why the ranking changed

The priority change can be explained quantitatively, but not by expected cost alone. Severity contributed equally across the four alternatives because all four causes were assigned severity 5, so severity could not discriminate among them.

Table 5. Corrected MAFMA total priorities and ranks

Cause	Severity	Occurrence	Detection	Exp. cost	Total	Rank
C1 Operator/SOP	0.06	0.07	0.02	0.05	0.20	2
C2 Cooling thread damage	0.06	0.05	0.02	0.05	0.17	3
C3 Inadequate mould design	0.06	0.09	0.01	0.30	0.47	1
C4 Recycled-material contamination	0.06	0.05	0.02	0.03	0.16	4

Occurrence favored C3 because inadequate mould design had the highest occurrence rating (5), while detection favored C1 because it had the highest detection rating (5). Expected cost then strongly amplified C3: its local expected-cost priority was 0.70 and expected cost received the largest criterion weight (0.43). Thus, the movement from C1 under conventional RPN to C3 under MAFMA-FAHP reflects the combined effect of unequal criterion weights and the added economic dimension, with expected cost providing the largest single contribution to C3's final score (Table 5).

This distinction is important because it prevents an over-interpretation of the cost term. A cost-sensitive model should not be accepted merely because it generates a different answer from RPN. The more relevant question is whether the preferred cause remains first when reasonable assumptions are changed. For that reason, a deterministic sensitivity analysis was added using the

reported local priorities. The expected-cost weight was varied by $\pm 20\%$ with the remaining weights renormalized proportionally; equal weighting and a no-cost scenario were also evaluated.

4.4 Sensitivity analysis

A cross all tested scenarios, C3 (inadequate mould design) remained the top-ranked cause. Under equal weights, C3 scored 0.368 compared with 0.230 for C1. Reducing the expected-cost weight by 20% still left C3 at 0.424, while increasing it by 20% raised C3 to 0.496. Importantly, even when expected cost was removed and the original S-O-D weight proportions were renormalized, C3 remained narrowly first (0.279 versus 0.263 for C1) (Table 6).

Table 6. Sensitivity of MAFMA ranking to criterion-weight assumptions

Equal weights	0.250	0.250	0.250	0.250	0.230	0.195	0.368	0.188	C3
Expected cost -20%	0.260	0.305	0.090	0.344	0.214	0.184	0.424	0.174	C3
Reported FAHP weights*	0.226	0.265	0.079	0.430	0.202	0.174	0.460	0.161	C3
Expected cost +20%	0.192	0.225	0.067	0.516	0.189	0.164	0.496	0.149	C3
No expected cost	0.397	0.466	0.138	0.000	0.263	0.223	0.279	0.223	C3

*The reported criterion weights sum to 1.01 because of rounding. For sensitivity calculations, S, O, and D were proportionally renormalized to the remaining weight after fixing expected cost. Scores are recomputed from rounded local priorities and are therefore not expected to reproduce the thesis totals exactly.

This shows that expected cost substantially strengthens the case for C3, but the priority is also supported by the FAHP weighting of occurrence relative to detection. The sensitivity result therefore supports robustness within the tested deterministic range while also showing that the exact score is weighting-dependent.

4.5 Implications for quality-risk prioritization

The central finding is that risk-prioritisation method selection can materially change the recommended improvement pathway. If management had used only

conventional FMEA, the natural response would have emphasized operator retraining, closer supervision, and tighter adherence to machine-setting procedures. These actions may still be appropriate, but the MAFMA-FAHP model indicates that they do not address the most consequential cause when expected cost is considered. The mould-design cause becomes dominant because it combines relatively high occurrence with a much larger cost implication. In practice, this can alter budget allocation, the required improvement team, and the time horizon of corrective action.

This finding is consistent with the broader literature criticizing unweighted RPN. Liu et al. (2013) and Huang et al. (2020) documented structural weaknesses in conventional RPN and the sustained development of weighting, fuzzy, and multi-criteria alternatives. More recent evidence strengthens that rationale: Chakhrit et al. (2024) showed that hybrid fuzzy-MCDM treatment can produce materially different failure rankings, while Shakibaei et al. (2024) explicitly incorporated failure cost into a fuzzy FMEA-MCDM framework. A 2025 systematic review likewise found continuing methodological emphasis on uncertainty modelling and multi-attribute ranking in FMEA-MADM research (Aleksić et al., 2025). The present case adds a manufacturing example in which the difference is not a marginal reshuffling but a change in the identity of the top-priority cause.

The result also supports Braglia's (2000) original motivation for MAFMA: criticality analysis benefits from considering expected cost alongside failure likelihood, non-detection, and severity. Nevertheless, the sensitivity analysis qualifies a simple 'cost caused the reversal' interpretation. Expected cost had the largest weight and contributed 0.30 of C3's reported 0.47 total, but C3 also remained first in the tested no-cost scenario after the original S-O-D weights were renormalized. The stronger conclusion is therefore that explicit weighting changes the decision logic, while expected cost materially reinforces the preference for the design-related cause. The weight of 0.43 should be interpreted as a case-specific expert preference rather than a universal constant.

4.6 Implications for injection-moulding improvement

Short shot is commonly associated with incomplete cavity filling caused by insufficient material flow before solidification, but troubleshooting cannot be reduced to one parameter. Hsiao et al. (2023) demonstrated that DMAIC combined with experimental analysis can identify injection speed and cooling time as decisive factors in plastic injection moulding, whereas more recent studies have used simulation, design of experiments, and AI-integrated Six Sigma to optimize multiple defect-related process parameters (Köken et al., 2026; Ratsaree & Chotiprayanakul, 2026). The present case differs because the decision problem was not only parameter optimization: the dominant defect was linked to a tooling-related failure mechanism. That distinction supports the use of a risk-prioritisation stage before committing resources to parameter adjustment alone. For the case manufacturer, the engineering interpretation of C3 was linked to recurring pin-shaft problems in the mould. A bent or broken pin-shaft could interfere with complete cavity filling and contribute to short shot. The original improvement project subsequently proposed a slider-based mould redesign. Because post-implementation performance data were not available within the study period, this manuscript deliberately

stops at risk-prioritisation and improvement selection. It does not claim that the redesign reduced defect rate. This boundary is important: identifying a justified improvement priority is distinct from experimentally validating the effectiveness of the implemented countermeasure.

From a DMAIC perspective, the distinction also clarifies the role of the Improve and Control phases. The present paper supports the selection of the improvement target and the rationale for engineering intervention. A complete closed-loop validation would require before-after production data after implementation, ideally including short-shot proportion, total defect rate, pin-shaft failure frequency, downtime, and cycle-time effects. Such data would allow the quality impact of the redesign to be tested rather than inferred.

4.7 Methodological lessons from re-analysis

Re-analysis of the original calculations produced three lessons relevant to applied quality research. First, mathematical checks should accompany spreadsheet-based FAHP calculations. A negative AHP consistency ratio is not evidence of exceptionally high consistency; it indicates that the eigenvalue/CI calculation should be re-examined. Recomputing the original matrices yielded positive CR values of 0.070 and 0.089, both acceptable under the conventional 0.10 rule.

Second, final ranks should be generated algorithmically from priority scores rather than entered manually. In the original table, 0.17 and 0.16 were labeled ranks 4 and 3, even though descending-score ranking requires the opposite. Such transcription errors are minor in terms of the top-priority conclusion but can undermine reviewer confidence. For publication-oriented industrial research, a reproducible calculation workbook or script is preferable to manual transfer of intermediate values.

A third lesson concerns aggregation and robustness. The reported total priorities correspond to the sum of weighted global contributions across criteria. Because weighted rankings can be sensitive to expert preference, the final decision should be accompanied by sensitivity analysis rather than presented as a deterministic truth. In this case the top rank was stable across $\pm 20\%$ changes in expected-cost weight, equal weighting, and a no-cost scenario, increasing confidence in the direction of the decision while not eliminating the uncertainty inherent in expert scoring.

4.8 Limitations and future research

Several limitations constrain generalization. The study is a single-product case from one manufacturing plant, and the pairwise weighting was elicited primarily from a production foreman rather than from a larger cross-functional expert panel. FAHP formalizes the judgment structure but cannot compensate for limited expert diversity. Consequently, the framework may be transferable, but the numerical weights and rankings should not be generalized beyond the case without local

re-elicitation. Future studies should use multiple experts from production, quality, tooling, maintenance, and finance and report inter-expert agreement or aggregation procedures.

The second limitation is the absence of validated post-implementation defect data. The selected mould-design intervention had entered the implementation stage after the academic project, but no sufficiently documented post-implementation production series was available for this study. Accordingly, this paper does not claim that the redesign reduced short-shot defects. Future work should compare defect rate, short-shot frequency, mould-related downtime, pin-shaft failure frequency, and maintenance cost before and after implementation, ideally using an interrupted time-series or matched production-run design.

Third, the model uses four MAFMA criteria and a deterministic sensitivity analysis based on rounded reported priorities. Additional attributes such as downtime, safety, maintainability, customer criticality, implementation time, and uncertainty in monetary estimates could be incorporated. Recent FMEA-MCDM research increasingly uses hybrid fuzzy and data-driven approaches to model such complexity (Aleksić et al., 2025; Chakhrit et al., 2024; Shakibaei et al., 2024). Probabilistic or Monte Carlo sensitivity analysis would be a useful extension when richer expert distributions or cost data are available.

4.9 Practical deployment framework

For practitioners, the combined method can be implemented as a five-step decision routine. First, use production data to identify a dominant CTQ and confirm that the selected problem represents a meaningful share of quality loss. Second, construct a cause map with operators, quality personnel, maintenance, and tooling specialists so that human, machine, material, method, and design mechanisms are all represented. Third, apply conventional FMEA as a transparent first screening step and document the evidence behind each S, O, and D rating. Fourth, apply MAFMA only to the manageable subset of actionable causes, adding expected cost and explicit criterion weights. Fifth, compare the two rank orders and investigate any reversal before authorizing corrective action. The comparison is itself useful because it shows whether the decision is being driven by technical criticality, frequency, detectability, or economic consequence.

When the top cause requires a capital or tooling intervention, as in the present case, the priority score should be followed by a business case rather than by immediate implementation. The business case should estimate intervention cost, expected reduction in failure frequency, avoided scrap, avoided downtime, maintenance effects, and implementation risk. Where possible, the organization should define a validation plan before the modification is made. For an injection mould, this may include a minimum trial quantity, acceptance limits for short-shot rate, dimensional inspection, pin-

shaft condition, cycle time, and a post-trial control-chart window. Such pre-specified metrics reduce the risk of declaring success based only on anecdotal operator feedback.

The framework can also be updated over time. Occurrence and detection ratings should change when new production evidence becomes available; expected-cost comparisons should be revised when repair prices, production volume, or downtime costs change. In this sense, MAFMA is most useful as a living prioritisation model rather than a one-time calculation. A spreadsheet implementation can be sufficient for small plants, provided formulas are protected and ranking is generated automatically. Larger organizations can embed the logic in quality-management dashboards, link failure causes to maintenance records, and perform periodic sensitivity tests to identify whether the recommended priority remains stable under plausible changes in criterion weights.

5. CONCLUSIONS

This study integrated DMAIC, FMEA, MAFMA, and FAHP to prioritize causes of injection-moulding defects in an automotive-component process. Baseline production records showed 85,016 units, 5,131 defective units (6.04%), and short shot as the dominant defect category (51.4%). Conventional FMEA ranked operator/SOP-related failure first (RPN 100), whereas MAFMA-FAHP ranked inadequate mould design first (total priority 0.47). Independent recalculation confirmed that the two underlying pairwise matrices were acceptably consistent ($CR=0.070$ and 0.089).

The change in priority was produced by the multi-attribute decision structure rather than by a single factor. Expected cost received the largest weight (0.43) and strongly amplified inadequate mould design through a 0.70 local cost priority, while occurrence weighting also favored the design-related cause. Sensitivity analysis showed that C3 remained first under equal weights, $\pm 20\%$ variation in expected-cost weight, and a no-cost scenario with the remaining FAHP weights renormalized. The practical implication is that industrial quality teams should test the robustness of a priority decision rather than relying on one RPN or one set of criterion weights.

The manuscript deliberately makes no claim that the subsequent mould redesign reduced defects because validated post-implementation data were unavailable. The contribution lies in the rigor of improvement selection. For industrial quality practice, the implication is straightforward: when competing failure causes require fundamentally different resources, quality teams should complement conventional FMEA with a transparent multi-attribute prioritisation model and verify the arithmetic before committing improvement expenditure.

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