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Sustainability Integration and Parameter Optimisation in Advancing Plastic Injection Moulding

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ABSTRACT

Injection moulding is a widely used method for manufacturing plastic components, with the quality of the final product depending on various process factors managed throughout the procedure. Integrating sustainable manufacturing practices is crucial for mitigating ecological impacts while maintaining product excellence. Manufacturers need to balance product quality, procedural effectiveness and environmental impact by evaluating how each parameter affects the product's quality and ecological footprint. While many focus on optimizing process parameters, fewer consider integrating sustainability competency, which also affects parameter performance. This study aims to advance understanding by conducting experiments and analyses on these factors' influence on product quality. The incorporation of sustainability competency aims to empower individuals and entities to make informed choices that align with environmental, societal and economic factors for a more sustainable and accountable future. The optimised model, with an error of less than 1%, quantifies the competency value bridging mechanical properties and comprehensive competency by integrating attitudinal factors. Parameter selection through Design of Experiments (DOE) and expert elicitation method contribute to this integration. Evolution from the foundational to the proficient model includes operational team and sustainability competency descriptors, providing context for innovation and knowledge creation highly valued by employers and stakeholders in a productive and streamlined setting.

1. Introduction

In the current manufacturing sector, sustainability is increasingly important, especially in injection moulding. This focus on sustainability combines eco-friendly methods, economic efficiency and social responsibility. It requires knowledge of sustainable materials, processes and design practices to lower environmental impact while ensuring high efficiency and product quality [1-4]. Critical aspects of sustainability in injection moulding include choosing the right materials, optimising processes, reducing waste, assessing product lifecycles, designing sustainably, adhering to regulations, striving

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for continuous improvement and maintaining effective communication. These elements address environmental issues and foster long-term success [5-8]. Recent research in sustainability spans various areas, including interdisciplinary approaches, advancements in education and training, development of assessment tools, insights from behavioural psychology, technology integration, corporate social responsibility, principles of the circular economy, policy impacts, social equity, supply chain management, stakeholder involvement and adaptability to environmental changes [9-13]. Keeping abreast of the latest academic research is crucial as the field evolves.

The Taguchi method has been extensively studied for its potential to improve the mechanical properties and manufacturing processes of plastic components [8,9]. Research has specifically focused on optimising parameters like melting temperature, injection pressure and cooling time to enhance the strength and quality of plastic products [10]. Adjustments to these factors have led to significant improvements in the tensile, compressive and flexural strengths of items such as plastic trays and containers made from recycled materials, proving that recycled plastics can be a viable alternative to virgin materials. Further refinement of process optimisation has been achieved by integrating the Taguchi method with simulation tools like Mould-Flow, enabling engineers to determine optimal parameters for increased energy efficiency and product quality [11,12]. Additionally, studies have demonstrated that the Taguchi method is effective in minimising defects such as weld lines and shrinkage, which enhances the quality and dimensional accuracy of plastic parts, an important consideration for industries requiring precise tolerances [13].

The Taguchi method has been investigated for its ability to enhance the mechanical properties of bio-composites and recycled composites. Many studies highlight its potential for promoting sustainable practices by optimising the use of recycled materials and refining composite performance through improved processing conditions [14]. Through a comprehensive analysis of how various factors affect material properties, researchers have determined the best process parameters to achieve greater impact strength and dimensional stability [15,16]. Furthermore, the method has effectively reduced part weight and minimised defects such as short shots, thus improving the efficiency and reliability of injection moulding processes [17]. In summary, the Taguchi method has emerged as a valuable tool for optimising injection moulding, leading to enhanced mechanical properties, fewer defects and higher-quality plastic parts, which in turn supports sustainable practices and boosts production efficiency in the plastics industry [18].

The passage emphasises the significance of sustainability practices and their various benefits. It highlights how adopting these practices can enhance brand reputation, attract customers, employees and investors, reduce costs, increase business resilience and create new market opportunities. The text also stresses the need for comprehensive strategies and frameworks, alongside the use of metrics to evaluate sustainable development. It underlines the importance of integrating knowledge and awareness into decision-making to effectively achieve sustainability goals. Specifically, in the context of Malaysia, the passage acknowledges the country’s efforts in advancing the Sustainable Development Goals (SDGs) and aligning them with national priorities. However, it also points out the need for detailed approaches, frameworks and indicators to address the challenges of interpreting sustainable development and setting suitable benchmarks within Malaysia. Overall, the passage advocates for the adoption of sustainable business practices, enhanced awareness and thorough strategies to reach development goals and ensure business success in Malaysia [19,20].

Sustainable manufacturing focuses on implementing technologies and practices that adhere to sustainability principles in economic, environmental and social dimensions. The primary goals of this approach are to minimise environmental impact through eco-friendly methods, reduce costs and product prices by using resources efficiently, lower energy consumption for economic and environmental gains, decrease waste to boost resource efficiency and reduce pollution, ensure safety to prevent workplace accidents and enhance worker health by improving workplace conditions [13]. Balancing the rising consumer demand with sustainability objectives supports both environmental responsibility and long-term economic viability. Given the significant contribution of manufacturing to global energy consumption and CO_2 emissions, it is essential to focus on reducing energy use and increasing the adoption of renewable energy sources. Achieving sustainability requires a comprehensive strategy at both the factory and process levels, including the use of data-driven approaches, technical adjustments for conserving energy and resources and the integration of energy-efficient technologies as alternatives to traditional practices [21-24].

The literature review identifies several key factors influencing the quality of plastic parts produced by injection moulding, including material selection, design considerations and processing parameters. Research has primarily focused on minimising defects, with particular attention to issues like warpage and shrinkage, often utilising the Taguchi method. Extensive studies have explored the impact of processing parameters on part quality, frequently using simulation tools to refine these effects. Additionally, some research has investigated how the Taguchi method can enhance the mechanical properties of composite materials. This study aims to advance beyond optimising individual characteristics by employing a composite desirability function to assess part quality in a more comprehensive manner. Expert elicitation plays a crucial role in capturing implicit judgments where empirical data is lacking, offering valuable insights for decision-making and modelling. Integrating sustainability into the optimisation of injection moulding processes poses challenges such as technical complexity and data limitations, requiring a collaborative approach to effectively address these issues.

This study explores how knowledge, attitudes and psychological factors interact within the context of sustainability, drawing on the theory of action to understand how perceptions of sustainability practices influence behaviour more than subconscious motives. It highlights the importance of both quantifying knowledge and considering qualitative aspects of attitudes towards best practices. Ramdas & Mohamed's framework integrates these factors, suggesting that willingness to engage in sustainability is linked to knowledge, awareness and attitudes [25]. The study also tackles challenges in using recycled materials in plastic manufacturing, particularly in injection moulding, where mechanical properties often suffer compared to virgin materials. By employing the Taguchi method to optimise injection moulding parameters and evaluating them through sustainability criteria, the research aims to enhance part quality and advance responsible manufacturing practices, focusing on thermoplastic polypropylene and excluding thermosets.

This study introduces a novel approach by incorporating the attitudinal parameter (λ) to evaluate the emotional tendencies and risk attitudes of design stakeholders, categorising them as risk-averse, risk-neutral or risk-seeking. Unlike traditional methods, this research emphasises the critical influence of attitudes on decision-making and sustainability practices, building on the theory of reasoned action and insights from Turan *et al.,* [7], Aikhuele *et al.,* [26,29,30], Lanang *et al.,* [27] and Ayasrah *et al.,* [28]. By linking attitudes to environmental concerns, personal values and motivations, the study provides a comprehensive framework for understanding decision-making dynamics. Furthermore, the integration of expert elicitation captures nuanced judgments, particularly in data-scarce scenarios, enhancing decision analyses with a blend of expertise and evidence. This innovative combination of attitudinal evaluation and expert-driven optimisation offers a significant advancement in embedding sustainable manufacturing practices into process optimisation, improving resource efficiency and minimising environmental impact in the plastic industry.

2. Methodology

The research is structured into three main phases: selecting process parameters and quality characteristics, optimising these parameters and integrating sustainability competencies into the characterisation of process parameters. The first phase describes the selection process for variables, including process parameters and quality characteristics. Optimisation is carried out in two stages: initially through Taguchi experiments and mechanical testing with S/N ratio analysis, followed by the application of the desirability function and verification studies. The next stage involves establishing quantitative relationships between process parameters and quality characteristics. Finally, the research examines how sustainability competencies are integrated into the characterisation of injection moulding parameters. The details of each phase are tabulated in Table 1, Table 2 and Table 3.

Table 1
Phase 1: Process parameter and quality characteristic selection

Aspect	Details
1. Focus	Selection of quality characteristics and process parameters for injection moulding.
2. Quality Characteristics	Dimensional properties, surface appearance, mechanical strength.
3. Primary Focus	Assessing tensile strength and flexural modulus of recycled polypropylene parts.
4. Key Parameters Identified	Melt temperature, injection pressure, injection speed, injection time, holding pressure, holding time, cooling time and mould temperature (constant).
5. Parameter Levels	Three levels selected for each factor to facilitate better analysis and optimisation.
6. Selection Basis	Industrial standards and preliminary testing to ensure acceptable dimensional properties and mechanical strength.
7. Parameter Values	Selected process parameters:

Factors	*Process Parameters*	*Level 1*	*Level 2*	*Level 3*
A	Melt temperature, °C	180	220	260
B	Injection pressure, MPa	45	50	55
C	Injection speed, mm/s	20	25	30
D	Injection time, Sec	6	7	8
E	Holding pressure, MPa	20	35	50
F	Holding time, Sec	1	2	3
G	Cooling time, Sec	15	20	25

Table 2
Phase 2: Optimising process parameters

Optimisation Method	Description
1. Taguchi Optimisation Method	Utilises Taguchi experiments and mechanical testing to optimise parameters.
2. Overall Desirability Function	Transforms each response into a dimensionless value, combining them into an overall desirability function using a relative weight scale.
3. Regression Analysis	Establishes quantitative relationships between product quality and process parameters.
4. Linear Regression	Preferred method for determining the impact of independent variables on the dependent variable.
5. R-squared Value	Measures the proportion of variability in the dependent variable explained by independent variables.
6. P-value	Indicates the significance of the correlations between variables.
7. Standard Error of the Coefficient	Provides insight into the precision of coefficient estimates. Smaller values indicate higher precision.

Table 3
Phase 3: Characterising process parameters

<table>
<tr><th>Aspect</th><th>Description</th></tr>
<tr><td>1. Basic Model for Forecasting Sustainability Competency</td><td>Integrates correlations between injection moulding parameters with a focus on sustainability competency.</td></tr>
<tr><td>2. Attitudinal Theory</td><td>Converts qualitative responses into quantitative data, categorising responses as Risk Averse, Risk Seeking or Neutral.</td></tr>
<tr><td>3. Interpretation from Scale to Attitudinal</td><td><table>
<tr><th>Scale</th><th>Value factor</th><th>Attitudinal response</th></tr>
<tr><td>Yes</td><td>1</td><td>Risk averse</td></tr>
<tr><td>No</td><td>-1</td><td>Risk seeking</td></tr>
<tr><td>Neutral</td><td>0</td><td>Neutral</td></tr>
</table></td></tr>
<tr><td>4. Job Design and Sustainability Competency</td><td>Incorporates job design and sustainability competency factors, with descriptors for different roles.</td></tr>
<tr><td>5. Job Design Based on Sustainability Competency Descriptors</td><td><table>
<tr><th>Job design</th><th colspan="2">Sustainability competency descriptors</th></tr>
<tr><th></th><th>Day shift</th><th>Night shift</th></tr>
<tr><td>Executive</td><td>W1</td><td>W4</td></tr>
<tr><td>Non-executive</td><td>W2</td><td>W3</td></tr>
</table></td></tr>
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3. Results
3.1 S/N Analysis

Table 4 and Table 5 present the rankings of process parameters' impact on tensile strength and flexural modulus, using signal-to-noise ratios. The delta value, calculated from highest and lowest averages for each factor, measures effect size. Melt temperature ranks highest for both qualities, followed by other factors like injection time and holding time. Injection pressure ranks lowest. For flexural modulus, the same trend is observed, with melt temperature being most influential and holding pressure least.

Table 4
Response table for the signal to noise ratio of tensile strength

Level	A	B	C	D	E	F	G
1	45.80	45.31	45.31	45.11	45.30	45.15	45.32
2	45.49	45.28	45.20	45.34	45.19	45.32	45.28
3	44.50	45.21	45.28	45.34	45.30	45.33	45.19
Delta	1.30	0.10	0.11	0.24	0.11	0.19	0.13
Rank	1	7	5	2	6	3	4

Table 5
Response table for the signal to noise ratio of flexural modulus

Level	A	B	C	D	E	F	G
1	79.82	79.58	79.68	79.64	79.67	79.53	79.63
2	79.72	79.68	79.59	79.60	79.65	79.75	79.69
3	79.43	79.70	79.69	79.72	79.64	79.67	79.64
Delta	0.39	0.12	0.10	0.12	0.03	0.22	0.07
Rank	1	3	5	4	7	2	6

The main effect plot of the signal-to-noise ratio highlights the most impactful values for each selected process parameter. Figure 1 illustrates the optimal process parameters for achieving the best tensile strength. The highest signal-to-noise ratio values for each parameter indicate the conditions that produce the highest quality response. According to Figure 1, the optimal injection moulding conditions for achieving maximum tensile strength are a melt temperature of 180°C, an injection time of 8 seconds, a holding time of 3 seconds, a cooling time of 15 seconds, an injection speed of 20 mm/s, a holding pressure of 20 MPa and an injection pressure of 45 MPa. These parameter values are selected based on their highest signal-to-noise ratio values, signifying their crucial role in obtaining the best quality response.

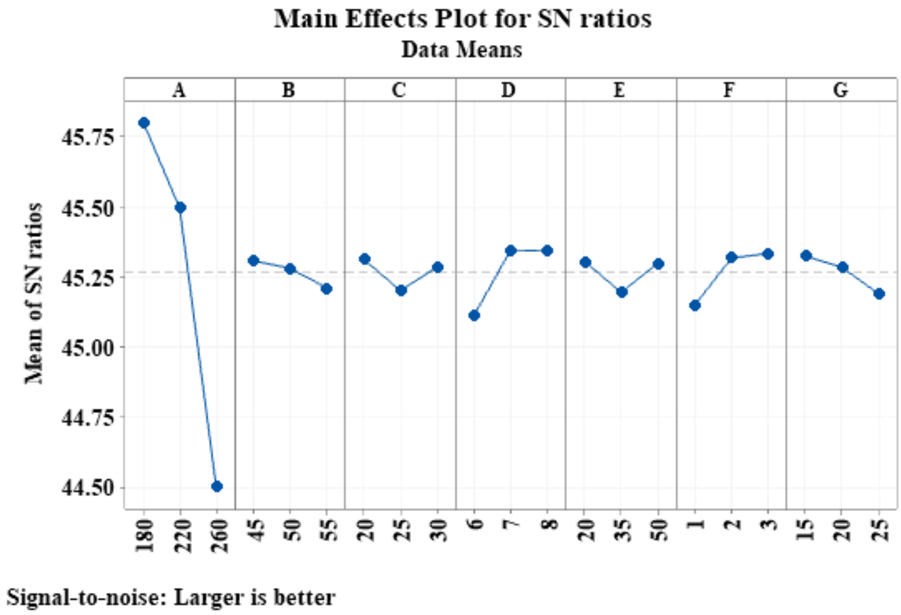

Fig. 1. Signal to noise ratio plot for tensile strength

According to Figure 1, the key factors affecting the tensile strength of recycled polypropylene (PP) are melt temperature, injection time and holding time. Specifically, lower melt temperatures have been found to improve tensile strength outcomes. For example, the highest tensile strength was consistently observed at the lowest temperature setting of 180°C. This improvement is likely due to reduced thermal degradation of the material during the injection moulding process, as noted by Gu *et al.,* [31]. Additionally, Figure 1 shows that increasing both injection time and holding time enhances tensile strength. Longer injection times allow for better control over the pressure increase within the runner and part cavity, leading to proper filling, improved appearance, part strength and dimensional accuracy, while also reducing residual stress. Lower residual stress contributes to better mechanical properties. Holding time, which correlates with cavity thickness, is also important; thicker products require longer cooling periods. Extended holding times ensure continuous resin filling, which helps avoid shrinkage and improves tensile strength.

In contrast, the flexural modulus is primarily influenced by melt temperature, with holding pressure being less significant. To optimise the flexural modulus, the optimal process parameters include a holding pressure of 20 MPa, a cooling time of 20 seconds, an injection speed of 30 mm/s, an injection time of 8 seconds, an injection pressure of 55 MPa, a holding time of 2 seconds and a melt temperature of 180°C. Figure 2 illustrates the signal-to-noise ratio plot, showing the impact of these parameters on the flexural modulus.

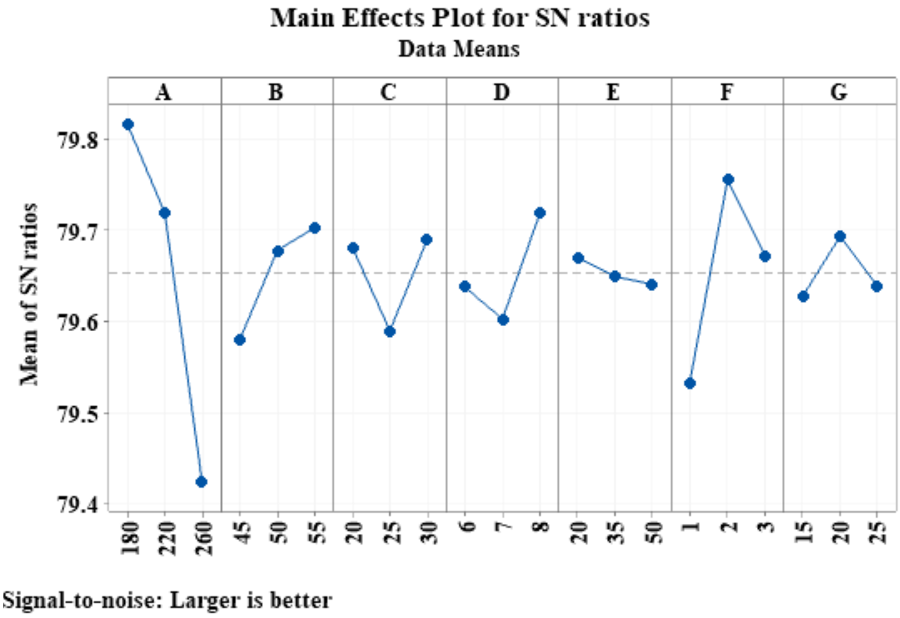

Fig. 2. Signal to noise ratio plot for Flexural modulus

3.2 Parameters Optimisation

The goal is to determine the optimal parameter values to maximise the overall desirability (D). Figure 3 and Figure 4 show the injection moulding process parameters that produce the best results for tensile strength and flexural modulus, respectively.

Fig. 3. Tensile strength as the response for individual optimisation

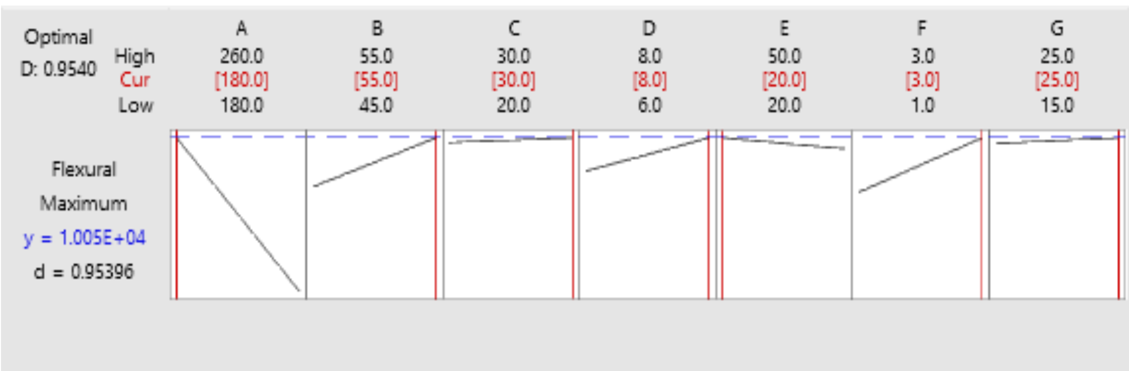

Fig. 4. Flexural modulus as the response for individual optimisation

After optimising for tensile strength and flexural modulus separately, both are combined using desirability functions to find the best parameters for both metrics together. For instance, a melt temperature of 180°C and a holding time of 3 seconds yield a tensile strength of 203.82 kgf/cm², while the same melt temperature and other parameters produce a flexural modulus of 10005 kgf/cm². Since the best parameters for each metric can differ, a composite desirability function method is used to determine a single set of parameters that optimises both. The final values, where both tensile strength and flexural modulus are optimised, are listed in Table 6.

Table 6
Results of multi response optimisation

Responses	Factors							Predicted responses	Desirability value
	A	B	C	D	E	F	G	(kgf/cm^2)	(kgf/cm^2)
Tensile strength	180	45	20	8	20	3	15	199	0.9767
Flexural modulus	180	55	30	8	20	3	25	10005	0.9767

A confirmation test was performed to ensure that the optimised process parameters produce the expected quality results. Although perfect accuracy is difficult to achieve due to repeatability issues, the test used the optimal parameters to compare with actual manufacturing outcomes. The same material properties were used as in the initial experiment to reduce variation. Three specimens were made using the optimised parameters and tested for tensile and flexural strength. The results were compared with expected values, showing good agreement as seen in Table 7. For example, the expected tensile strength was 199 kgf/cm², while the measured strength was 197 kgf/cm², with a 1% error. The flexural modulus had a very small error of 0.03%. This test confirms that the optimisation approach is effective and the parameters reliably achieve the desired quality.

Table 7
Confirmation test of optimised parameters

Responses	Predicted results (kgf/cm^2)	Confirmation results (kgf/cm^2)	Error (%)
Tensile strength	199	197	1
Flexural modulus	10005	10002	0.03

3.3 Regression Analysis

Regression analysis is used to explore the relationship between variables, with the R-square value or correlation coefficient, typically ranging from 0.8 to 1 in multiple linear regression. This value is important for predicting future outcomes based on similar data, indicating how well the model forecasts results. In this study, the correlation between process parameters and quality attributes was modelled, with Table 8 and Table 9 detailing the coefficients for each injection moulding parameter and their effects on tensile strength and flexural modulus.

Table 8
Coefficient of prediction model for tensile strength

Term	Coefficient	SE Coefficient	T-Value	P-Value	VIF
Constant	253.3	17.0	14.89	0.000	
Melt temperature	-0.3373	0.0280	-12.04	0.000	1.00
Injection pressure	-0.173	0.224	-0.77	0.449	1.00
Injection speed	-0.055	0.224	-0.24	0.810	1.00
Injection time	2.31	1.12	2.07	0.053	1.00
Holding pressure	-0.0039	0.0747	-0.05	0.959	1.00
Holding time	1.83	1.12	1.64	0.118	1.00
Cooling time	-0.253	0.224	-1.13	0.274	1.00

Table 9
Coefficient of prediction model for flexural modulus

Term	Coefficient	SE Coefficient	T-Value	P-Value	VIF
Constant	9603	735	13.07	0.000	
Melt temperature	-5.37	1.21	-4.44	0.000	1.00
Injection pressure	13.71	9.69	1.42	0.173	1.00
Injection speed	1.29	9.69	0.13	0.895	1.00
Injection time	46.5	48.4	0.96	0.349	1.00
Holding pressure	-1.04	3.23	-0.32	0.751	1.00
Holding time	75.9	48.4	1.57	0.134	1.00
Cooling time	1.60	9.69	0.17	0.870	1.00

To ensure the accuracy of a regression-derived mathematical model for manufacturing processes, it must undergo validation. An experiment was conducted following the same setup as previous tests and mechanical tests were performed accordingly. Table 10 presents the verification results: the model predicted a tensile strength of 197.19 kgf/cm² and a flexural modulus of 9827.05 kgf/cm², while the actual measured values were 197.26 kgf/cm² and 9875.88 kgf/cm², respectively. The error percentages for tensile strength and flexural modulus were 0.03% and 0.4%, both under 2%. These results highlight the model's practical reliability and effectiveness.

Table 10
Confirmation test of regression model

Responses	Factors							Predicted results (kgf/cm^2)	Confirmation results (kgf/cm^2)	Error (%)
	A	B	C	D	E	F	G			
Tensile strength	180	50	25	7	35	2	20	197.19	197.26	0.03
Flexural modulus	180	50	25	7	35	2	20	9827.05	9875.88	0.4

3.4 Integrating Sustainability Competency (Characterisation)

The model developed in Phase 2, which focuses on functional aspects, lacks the depth needed to drive innovation due to its omission of staff roles within their groups. It fails to address crucial behavioural elements like trust and honesty, essential for effective informal knowledge creation. As noted in Phase 1, the process parameters in Phase 2 are based solely on mechanical properties. To address this gap, introducing a sustainability competency definition is necessary. This definition aims to create a competency model that incorporates staff roles and integrates trust and honesty. By including these attitudinal factors "Knowledge" and "Behaviour" through expert elicitation, the model is refined to enhance its predictive accuracy. This improvement, detailed in Table 11, strengthens the model's ability to account for the complex interplay between these attributes and their impact on knowledge creation.

Table 11
Job design weightage for knowledge and attitudinal behaviour

Job design	Weightage	
	Knowledge	Behavioural
Executive	0.49	0.52
Non-executive	0.47	0.67

The job design has been refined to include staff functions through a sustainability competency definition and the addition of attitudinal factors such as knowledge and behaviour. Predictive equations, detailed in Table 12 and Table 13, form a comprehensive model that captures the complex interactions between staff roles, attitudinal factors and job design.

Table 12
Characterisation of operational team for knowledge and attitudinal behaviour (Tensile strength)

Phase	Operational team	Characteristic (predictive) model
Before characterised	-	TS= 253.3 - 0.3373 A - 0.173 B- 0.055 C + 2.31 D - 0.0039 E + 1.83 F - 0.253 G
After characterised	W1	Wk1 = 116.72 – 0.1567 A - 0.0516 B + 0.0058 C + 0.9288 D + 0.0074 E + 0.8097 F - 0.0990 G
		Wb1 = 129.14 - 0.1733 A - 0.0570 B + 0.0060 C + 1.0280 D + 0.0081 E + 0.8960 F - 0.1090 G
	W2	Wk2 = 125.15 - 0.1660 A - 0.0749 B - 0.0457 C + 1.0276 D - 0.0090 E + 0.6307 F - 0.0915 G
		Wb2 = 166.39 – 0.2234 A - 0.0736 B + 0.0083 C + 1.3240 D + 0.0105 E + 1.1543 F – 0.1411 G
	W3	Wk3 = 119.91 - 0.1596 A - 0.1054 B + 0.0390 C + 1.2713 D - 0.0042 E + 1.0912 F - 0.1537 G
		Wb3 = 170.94 - 0.2275 A - 0.1503 B - 0.0556 C + 1.8123 D - 0.0060 E + 1.5555 F – 0.2191 G

* Wk = knowledge, Wb = behaviour, TS = tensile strength

Table 13
Characterisation of operational team for knowledge and attitudinal behaviour (Flexural modulus)

Phase	Operational team	Characteristic (predictive) model
Before characterised	-	FM = 9603 - 5.37 A + 13.71 B + 1.29 C + 46.5 D - 1.04 E + 75.9 F + 1.60 G
After characterised	W1	Wk1 = 4339 - 2.56 A + 7.36 B - 1.30 C + 38.46 D + 0.56 E + 43.89 F + 1.83 G
		Wb1 = 6186 – 3.65 A -3.65 B - 1.85 C + 54.80 D + 0.80 E + 62.60 F + 2.61 G
	W2	Wk2 = 4025 - 2.26 A + 13.14 B + 6.79 C + 7.77 D - 1.16 E + 29.65 F + 3.15 G
		Wb2 = 5738 – 3.23 A + 18.73 B + 9.68 C + 11.10 D - 1.65 E + 42.30 F + 4.49 G
	W3	Wk3 = 5395 - 2.90 A - 0.99 B – 4.05 C + 20.13 D - 0.83 E + 33.87 F - 2.83 G
		Wb3 = 5726 - 3.08 A - 1.04 B - 4.30 C + 21.4 D - 0.88 E + 35.9 F - 3.00 G

* Wk = knowledge, Wb = behaviour, FM = flexural modulus

The R-squared (R^2) coefficient evaluates how well a regression model fits the data by showing how effectively the predictors explain the response. Table 14 and Table 15 present the R^2 values for the tensile strength and flexural modulus models. Models that include sustainability competency definitions and attitudinal factors consistently show high R^2 values, indicating they account for a significant portion of the variability in competency dimensions. The results from the characterised model underscore the importance of integrating staff attitudes towards knowledge creation with mechanical properties, as defined by the optimised parameters in Phase 2.

Table 14
R-squared (R^2) assessment result for all tensile strength

Job design	Operational team	Before characterisation		After characterisation			
				Knowledge		Behaviour	
		R^2	R^2 (adj)	R^2	R^2 (adj)	R^2	R^2 (adj)
Executive	W1	89.00%	85.00%	89.03%	84.99%	89.03%	84.99%
Non-executive	W2			86.58%	82.56%	88.25%	84.72%
	W3			85.59%	81.27%	86.49%	82.43%

Table 15
R-squared (R^2) assessment result for all flexural modulus

Job design	Operational team	Before characterisation		After characterisation			
				Knowledge		Behaviour	
		R^2	R^2 (adj)	R^2	R^2 (adj)	R^2	R^2 (adj)
Executive	W1	57.00%	57.00%	56.30%	40.19%	56.30%	40.19%
Non-executive	W2			52.69%	35.26%	52.69%	35.26%
	W3			45.70%	25.69%	45.70%	25.69%

3.5 Summary

The experiment followed the Taguchi design, assessing the mechanical properties of recycled polypropylene, such as tensile strength and flexural modulus. Signal-to-noise ratio analysis identified melt temperature, injection time and holding time as the key factors affecting tensile strength, with injection pressure having the least impact. For flexural modulus, melt temperature, holding time and injection pressure were the most significant. Optimisation using desirability functions set the ideal parameters as 180°C melt temperature, 55 MPa injection pressure, 30 mm/s injection speed, 8 seconds injection time, 20 MPa holding pressure, 3 seconds holding time and 25 seconds cooling time, resulting in a tensile strength of 199 kgf/cm² and a flexural modulus of 10005 kgf/cm². A confirmation test showed minimal errors of 1% for tensile strength and 0.03% for flexural modulus. Additionally, regression analysis of the relationship between process parameters and mechanical properties produced errors of 0.03% and 0.4% for tensile strength and flexural modulus, respectively, confirming the model's accuracy. The final phase compared the predictive model to the basic model, showing no significant differences, validating the sustainability competency model for evaluating knowledge creation in injection moulding.

4. Conclusions

This research explores how job design and attitudinal factors interact through predictive models that integrate algorithms. By using data from experiments and questionnaires on process parameters and competency performance, the study examines the links between job design, operational teams and sustainability competencies in injection moulding. The research introduces a characterised model that includes attitudinal elements like knowledge and behaviour, enhancing the model's ability to predict competency performance. Regression analysis compares the basic model to the characterised model, showing that adding attitudinal factors improves the model's effectiveness. The study also identifies optimal injection moulding parameters, validates them through experiments and confirms their accuracy with minimal error rates. This comprehensive approach integrates mechanical properties with sustainability competencies, providing a robust framework for assessing and improving job design and process optimisation.

This research focuses on optimising process parameters for enhancing the mechanical properties of recycled materials using Taguchi experimental design and the desirability function approach. Future research should investigate additional mechanical properties such as impact and compression strength and optimise parameters for various material properties, including melt flow index, while considering different suppliers and batches. It is also important to explore the repeatability of optimised parameters and incorporate advanced techniques like scanning electron microscopy (SEM) for more precise data. Further study should examine interactions between process parameters, mould temperature and machine settings, as well as explore parameter optimisation for compounded materials to address compatibility issues. The newly developed characterised model for predicting sustainability competency highlights the importance of measurable integration and could lead to the establishment of quality metrics and innovations in the injection moulding industry, supporting regional economic growth.

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