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Influence of Human Factors Engineering on Scrap Optimization in Manufacturing Industry: An Empirical Investigation

Talvinder Singh Kalsi
M.Tech. Research Scholar
Industrial Engineering
Takshshila Institute of Engineering and Technology
Jabalpur (M.P.), India
Email: talvindersingh0013@gmail.com

Alok Agrawal
Assistant Professor
Department of Mechanical Engineering
Takshshila Institute of Engineering and Technology
Jabalpur (M.P.), India
Email: alokagrawal26318@gmail.com

Abstract—*Manufacturing industries continuously strive to improve productivity, product quality, and operational efficiency while minimizing material waste and production costs. Scrap generation remains a critical challenge directly impacting profitability and sustainability. While technological advancements have enhanced automation, human-related factors—such as operator competency, ergonomics, fatigue, communication, and adherence to Standard Operating Procedures (SOPs)—continue to govern defect rates. Human Factors Engineering (HFE) provides a systematic approach to optimizing human-machine-environment interactions. This study empirically investigates the relationship between five core HFE dimensions (Ergonomics, Operator Competency, Human Error Management, Work Environment, and Organizational Support and Safety) and Scrap Optimization in manufacturing firms (N = 60). Statistical analyses including reliability testing (α = 0.918), Pearson correlation, Exploratory Factor Analysis (EFA), and multiple regression demonstrate that HFE practices account for 79.6% of the variance in scrap reduction (R_2= 0.796, F = 41.284, p <0.001). Organizational Support and Safety (β = 0.371) and Operator Competency (β = 0.332) emerged as the strongest predictors. An integrated implementation frame work is proposed to support sustain able waste reduction.*

Keywords:— *Human Factors Engineering, Ergonomics, Scrap Optimization, Manufacturing Process Improvement, Human Error Management, Multiple Regression Analysis.*

1. INTRODUCTION

Manufacturing industries represent a vital pillar of economic development, transforming raw materials into value-added outputs through complex combinations of technology, machinery, and human capital. Production efficiency and profitability are inherently tied to resource utilization and waste minimization. Despite substantial investments in lean manufacturing, Total Quality Management (TQM), and Industry 4.0 automation, manufacturing scrap remains a persistent financial and operational bottleneck.

Traditionally, scrap reduction initiatives have prioritized machine parameter optimization, tool design, and material specification, while frequently overlooking the fundamental impact of Human Factors Engineering (HFE). In manual, semi-automated, and supervisory manufacturing setups, human operators make real-time decisions, manage machine setups, handle material transfers, and execute quality inspections. Deficiencies in workstation layout, physical fatigue, cognitive overload, inadequate training, and unclear communication increase operator vulnerability to errors, resulting in dimensional inaccuracies, product defects, rework, and excessive scrap.

HFE applies knowledge regarding human capabilities, limitations, and behaviors to the design of workstations, tools, tasks, and organizational environments. By addressing physical, cognitive, and organizational ergonomics, manufacturing enterprises can build resilient work systems that systematically prevent defect generation.

2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

The theoretical foundation of human error prevention in industrial operations rests upon established socio-technical and ergonomics models:

- **Swiss Cheese Model and HFACS:** Reason's Swiss Cheese Model posits that industrial defects result from an alignment of latent organizational weaknesses and active operator errors. The Human Factors Analysis and Classification System (HFACS) operationalizes this by categorizing errors into unsafe acts, preconditions (fatigue, environmental stressors), supervisory gaps, and organizational influences.
- **Systems Engineering Initiative for Patient Safety (SEIPS 2.0):** Demonstrates how interactions between people, tasks, tools, environments, and organizational conditions directly shape operational outcomes.
- **Functional Resonance Analysis Method (FRAM):** Captures how everyday work variability across operators, equipment, and ambient conditions resonates to produce operational defects or quality breakthroughs.

Empirical studies in manufacturing systems emphasize that while process parameter optimization reduces technical variability, operator execution remains paramount. Research by Groover, Kalpakjian and Schmid, and Bhamu and Sangwan highlights that industries with significant manual involvement require robust HFE interventions to mitigate operator fatigue, standardize procedures, and ensure sustainable lean implementation.

3. RESEARCH METHODOLOGY AND CONCEPTUAL MODEL

This research adopts a quantitative, empirical design to evaluate the influence of HFE dimensions on manufacturing scrap optimization.

3.1 Variables and Hypotheses

The conceptual framework evaluates five Independent Variables (IVs) representing core HFE dimensions against one Dependent Variable (DV), Scrap Optimization:

- **Ergonomics (ERG):** Workstation layout, posture, manual material handling, tool accessibility.
- **Operator Competency (OC):** Skill levels, technical training, operational experience, continuous learning.
- **Human Error Management (HE):** Procedural compliance, error detection mechanisms, fatigue mitigation.
- **Work Environment (WE):** Thermal comfort, lighting, noise control, ventilation, cleanliness.
- **Organizational Support and Safety (OS):** Management commitment, safety culture, supervisory guidance, teamwork.
- **Scrap** Optimization **(SO):** Material waste reduction, defect minimization, rework reduction, overall process

quality.

The study tests five primary hypotheses (H_1–H_5), proposing that each HFE dimension significantly and positively influences Scrap Optimization.

3.2 Sample and Demographics

Data was gathered via a structured 5-point Likert scale instrument (1 = Strongly Disagree to 5 = Strongly Agree) administered across manufacturing facilities. The final sample comprises N = 60 qualified industry personnel across diverse sectors and functional designations. Table 1outlines respondent demographics.

4. EMPIRICAL RESULTS AND STATISTICAL ANALYSIS

4.1 Reliability and Construct Validity

Construct reliability was assessed using Cronbach's Alpha (α). As detailed in Table 2, all individual constructs demonstrated high internal consistency (α >0.80), with the overall 20- item survey instrument exhibiting exceptional reliability (α =0.918).

Table 1: Demographic Profile of Survey Respondents (N = 60)

Demographic Variable	Category	Frequency	Percentage (%)
Gender	Male	48	80.0
	Female	12	20.0
Age Group	Below 25 years	8	13.3
	25–35 years	24	40.0
	36–45 years	18	30.0
	Above 45 years	10	16.7
Qualification	Diploma	15	25.0
	Bachelor's Degree (B.E. / B.Tech)	26	43.3
	Master's Degree (M.E. / M.Tech / MBA)	15	25.0
	Other	4	6.7
Industry Sector	Automobile	16	26.7
	Steel and Metal	10	16.7
	Machine Tools	9	15.0
	Electronics	8	13.3
	Plastic and Polymer	7	11.7
	Food Processing / Pharma / Textile	10	16.6
Experience	Less than 2 years	7	11.7
	2–5 years	19	31.7
	6–10 years	18	30.0
	More than 10 years	16	26.6

Table 2: Construct Reliability and Descriptive Statistics

Construct	Items	Mean Score	Cronbach's α	Interpretation
Ergonomics (ERG)	Q1–Q3	3.86	0.842	Good Reliability
Operator Competency (OC)	Q4–Q6	3.82	0.861	Good Reliability
Human Error Management (HE)	Q7–Q9	3.87	0.823	Good Reliability
Work Environment (WE)	Q10–Q12	3.86	0.851	Good Reliability
Organizational Support (OS)	Q13–Q15	3.84	0.878	Good Reliability
Scrap Optimization (SO)	Q16–Q20	3.92	0.904	Excellent Reliability
Overall Questionnaire	**Q1–Q20**	**3.86**	**0.918**	**Excellent Reliability**

Exploratory Factor Analysis (EFA) using Varimax rotation confirmed structural construct validity. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.893, and Bartlett's Test of Sphericity was highly significant ($\chi^2 = 812.476$, $df = 190$, $p < 0.001$). Six distinct factors were extracted, explaining 76.68% of the cumulative variance.

Table 3: Pearson Correlation Matrix ($N = 60$)

Variables	ERG	OC	HE	WE	OS	SO
Ergonomics (ERG)	1.000	0.612**	0.548**	0.665**	0.589**	0.731**
Operator Competency (OC)	0.612**	1.000	0.638**	0.596**	0.681**	0.784**
Human Error (HE)	0.548**	0.638**	1.000	0.571**	0.624**	0.695**
Work Environment (WE)	0.665**	0.596**	0.571**	1.000	0.642**	0.748**
Organizational Support (OS)	0.589**	0.681**	0.624**	0.642**	1.000	0.801**
Scrap Optimization (SO)	0.731**	0.784**	0.695**	0.748**	0.801**	1.000

** Correlation is significant at the 0.01 level (2-tailed).

4.2 Correlation Analysis

Pearson correlation coefficients (r) were computed to evaluate bivariate relationships among constructs. All HFE dimensions exhibited strong, statistically significant positive correlations with Scrap Optimization ($p < 0.001$), as reported in Table 3.

4.3 Multiple Regression Analysis and Hypothesis Testing

Multiple linear regression was conducted to model Scrap Optimization as a function of the five HFE dimensions:

$$SO = \beta_0 + \beta_1(ERG) + \beta_2(OC) + \beta_3(HE) + \beta_4(WE) + \beta_5(OS) + \epsilon \quad (1)$$

The regression model proved highly significant (F (5, 54) = 41.284, $p < 0.001$), explaining 79.6% of the total variance in scrap optimization ($R^2 = 0.796$, Adjusted $R^2 = 0.777$, Standard Error = 0.318). Multicollinearity was ruled out a sall Variance Inflation Factors (VIF) remained well below the threshold of 3.0 ($1.64 \leq VIF \leq 1.95$).

Table 4: Multiple Regression Coefficients and Hypothesis Testing Summary

Predictor Construct	Unstd. B	Std. Error	Std. Beta (β)	t-value	p-value	Hypothesis Decision
(Constant)	0.482	0.296	—	1.628	0.109	—
Ergonomics	0.184	0.063	0.221	2.921	0.005	H1 Supported
Operator Competency	0.268	0.059	0.332	4.542	<0.001	H2 Supported
Human Error Management	0.143	0.057	0.186	2.503	0.015	H3 Supported
Work Environment	0.201	0.061	0.257	3.295	0.002	H4 Supported
Organizational Support and Safety	0.294	0.056	0.371	5.286	<0.001	H5 Supported

Table 4 details the regression coefficients and hypothesis testing decisions. All five hypotheses (H_1–H_5) were statistically supported (p <0.05).

Figure 1 visually compares the standardized impact (β) of each HFE dimension on scrap reduction. Organizational Support and Safety exerts the largest relative influence (β = 0.371), closely followed by Operator Competency (β =0.332).

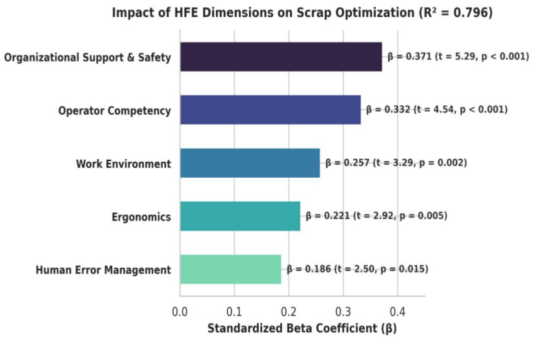

Figure 1: Relative Impact of HFE Dimensions on Scrap Optimization (Standardized Beta Co- efficients).

5. PROPOSED HFE IMPLEMENTATION FRAMEWORK

Based on the empirical findings, an integrated, four-phase HFE framework is proposed for manufacturing organizations to achieve systematic scrap reduction:

Phase I: Assessment and Baseline Measurement: Conduct ergonomic risk assessments (REBA/RULA), map human error points via Fishbone/FMEA, and benchmark initial scrap rates.

Phase II: Targeted HFE Interventions: Redesign physical workstations to minimize awkward postures; implement structured SOP training and operator skill matrix updates; improve ambient lighting, ventilation, and noise abatement.

Phase III: Monitoring and Performance Evaluation: Audit procedural compliance, track real-timemachinedefectlogs,andimplementsupervisoryfeedbackloops.

Phase IV: Continuous Improvement and Cultural Embedding: Integrate HFE into Lean Six Sigma DMAIC projects, foster safety/quality leadership, and update standards based on operator feedback.

Figure 2 depicts the sequential flow of the integrated HFE framework.

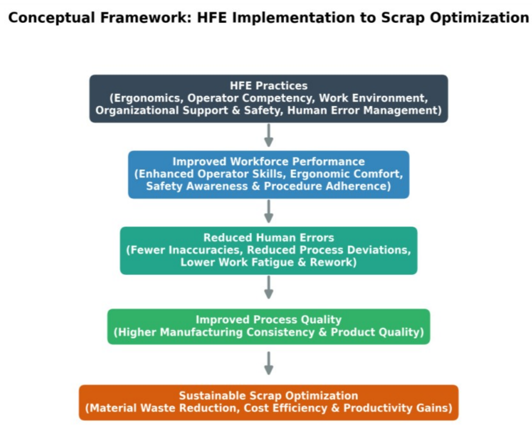

Figure 2: Conceptual Framework: Sequential Impact of HFE Interventions on Scrap Optimization.

6. DISCUSSION AND MANAGERIAL IMPLICATIONS

The empirical results confirm that scrap optimization cannot be achieved purely through technological fixes. Human operators represent the critical operational link where quality is either preserved or compromised.

Management commitment and safety support (β = 0.371) surfaced as the primary catalyst for scrap reduction. When leadership actively supports safety practices, provides supervisory guidance, and fosters open communication, operators display high reengagement and care during process execution. Similarly, operator competency (β = 0.332) ensures that workers possess the technicalacuitytodetectminorprocessdriftbefor edefectiveoutputaccumulates.

Ergonomic workplace design (β = 0.221) and environmental control (β = 0.257) directly alleviate physical fatigue and cognitive strain. In high-repetition manufacturing setups, fatigue significantly increases human error rates; ergonomic interventions neutralize these latent risk conditions.

7. CONCLUSION AND FUTURE RESEARCH

This research establishes robust empirical evidence that Human Factors Engineering plays a pivotal role in optimizing scrap generation in manufacturing industries. HFE dimensions collectively explain 79.6% of variance in scrap reduction. Integrating ergonomic principles, competency development, environmental management, and organizational safety culture creates a highly reliable manufacturing ecosystem that minimizes material waste and elevates product quality.

7.1 Future Research Directions

Future studies can build upon these findings by:

- Expanding sample sizes across broader geographical regions and small-to-medium enterprises (SMEs).
- Utilizing Structural Equation Modeling (SEM) to explore potential mediating mechanisms (e.g., operator fatigue or job satisfaction).
- Investigating the synergy between HFE interventions and digital Industry 4.0 technologies (e.g., AI-assisted inspection, augmented reality assembly guides).

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