

Lean Six Sigma and Zero Defects: An Entropy-Based Approach to Optimizing Productivity in Modern Manufacturing Processes

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Abstract: The order gets transformed into disorder in the process of production; this disorder may show up in different forms, including process variability, unexpected occurrence of changeovers, rework loops, and instability in scheduling. The authors interpret this disorder in terms of process entropy and examine its connection to productivity in manufacturing plants that are employing the Lean Six Sigma (LSS) techniques formally. The data on the survey was collected from the manufacturing professionals and analyzed using the PLS-SEM SmartPLS 4. The analysis considered five reflective variables for each construct there were, namely, Process Entropy (PE), Manufacturing Productivity (MP), and Zero Defects Orientation (ZDO). The measurement model has shown positive internal consistency scores (0.740–0.844) and the composite reliability of over 0.824 but the construct ZDO has demonstrated a lower validity result compared to the rest of the constructs in terms of the criteria. The structural model explains 58.7 % and 66.8 % of the variance in MP and ZDO, respectively being considerable on size both ($f^2 = 1.423$; $f^2 = 2.012$). Discriminant validity is absent between PE and ZDO that indicates that the instrument used in the study did not create the possibility to differentiate between PE and ZDO phenomena.

Keywords: Lean Six Sigma; process entropy; zero defects; manufacturing productivity; PLS-SEM; overall equipment effectiveness

1. INTRODUCTION

The 21st century manufacturing competitive landscape is largely determined by the capacity to achieve production improvement in line with the control of quality, resource management and process complexity. Thus, Lean Six Sigma (LSS) has emerged as a valuable tool for operational excellence, combining the principles of Lean manufacturing for waste reduction and the focus on value flow with the statistical control of process variation principles of Six Sigma. It has been reported to have a beneficial effect on various manufacturing dimensions such as productivity, process efficiency, quality and decision making in various industrial sectors [14]–[17], [24], [25]. Current manufacturing is becoming more digital, and more demanding in terms of sustainability, however, the challenges of current manufacturing processes also show the shortcomings of viewing productivity and quality, sustainability and process complexity as largely independent improvement targets.

New study shows the trend toward integrated improvement architectures. For instance, validation of Lean–Green–Six Sigma model in an Indian manufacturing context [2] shows that operational and environmental improvement can be combined to gain not only performance benefits but also sustainability benefits. Likewise, Green Lean Six Sigma research focuses on systematically selecting and implementing improvement projects based on several sustainability-related criteria [8] and entropy-based TOPSIS has been used to prioritize sustainable development approaches in manufacturing [9]. The developments are a sign of the growing need for methods in modern manufacturing that can take into account various aspects of the process performance, not just optimize a single



performance indicator. This need is enhanced by Industry 4.0. Manufacturing systems can produce and process significantly more operational information through artificial intelligence (AI), Internet of Things (IoT), advance analytics and interconnection of production technologies [6] and [11]. Digital technologies enable predictive maintenance, process monitoring, adaptive production and better-quality management, which opens up opportunities for increased productivity and responsiveness [6]. Meanwhile, digital and smart manufacturing also poses new problems such as system interoperability, organizational capacity, measurement disintegration and the complexity of the manufacturing process [3, 11]. In recent literature, there has been a demand to combine these three approaches of lean efficiency, sustainable lifecycle thinking and digitally supported feedback mechanisms into a single process, instead of keeping them separate improvement programs [3], [4].

Quality is one of the basic elements of this change. Defects, rework, resource losses, extra processing needs, customer satisfaction, and organizational reputation are just some of the negative consequences of poor quality [6]. The application of traditional quality-management techniques such as Lean manufacturing, Six Sigma, Total Quality Management, and other related techniques has brought significant benefits; however, these techniques focus only on one aspect of the ever more integrated manufacturing system or another, and do not necessarily represent the whole picture. This limitation is especially significant because manufacturers are rapidly transitioning to the age of data-driven manufacturing, where machine, material, method and man are working together throughout the production process. To overcome this challenge, the Zero-Defect Manufacturing (ZDM) paradigm has been introduced, which is a paradigm that puts an emphasis on quality management in a manner that is shifted from the end-of-line to the prevention and compensation part of the production system. Defect prevention and defect compensation are two key strategies for ZDM, and Industry 4.0 technologies offer a promising future in the field of zero-defect processes that can be extended to the wider realm of zero-waste manufacturing systems [5]. Recent studies further extend the human-centred aspect of ZDM, and it is found that besides technological issues, the human aspects of the production system need to be taken into account when aiming for zero defects [23]. In this regard, ZDM expands the quality goal of LSS by making the elimination/prevention of defects a part of the manufacturing process, not just of quality control.

Fig. 1 summarizes this trajectory, situating Lean Six Sigma and Zero Defect Manufacturing within the broader evolution of quality-management and manufacturing paradigms.

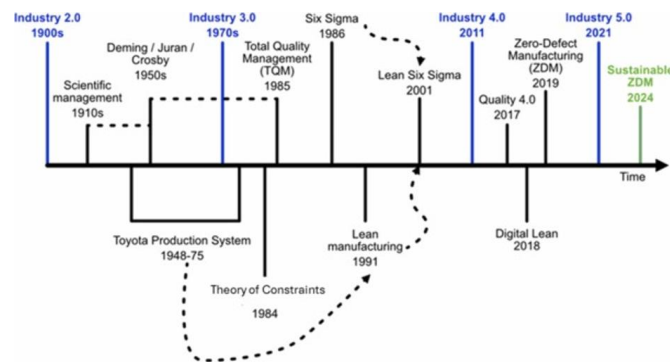


Fig. 1. Evolution of quality-management and manufacturing-improvement paradigms from Industry 2.0 to Industry 5.0, leading to Lean Six Sigma and Zero-Defect Manufacturing.

Although significant progress has been made, there is an important conceptual gap that needs to be addressed. Many of the current LSS and ZDM practices use metrics such as defect rates, process capability indices, statistical process control indices, productivity measures, and value stream metrics. These are useful for quantifying specific aspects of performance, but do not necessarily give a common quantitative measure of the overall disorder or uncertainty induced by the various types of manufacturing process. The importance of this becomes more pronounced as variability comes at the same time from machines, materials, methods, information flows, environmental conditions and human interventions. The studies on manufacturing information fields and complexity management also indicate that the structure, distribution and complexity of the information and process states affect manufacturing performance

[1], [11]. Therefore, a metric that can describe uncertainty in the process in a way that can be compared between various sources and operating conditions is needed.

This is where information theory can offer a potentially useful basis for tackling this gap. The Shannon uncertainty is a measure of the amount of uncertainty or unpredictability in a probability distribution and thus can be used as a mathematically defined measure for the spread of the process states. In the manufacturing context, entropy has been used in decision making and project prioritization [9] [10] and modelling uncertainty and complexity in production and supply chain environments [11] [12]. More directly, an entropy-based Lean–Energy–Six Sigma value-stream mapping approach has been shown to be feasible to identify workstations or reject and rework in a value stream while simultaneously taking into account energy and waste [7]. Studies on entropy in process science also indicate that entropy can offer a theoretical framework to see the disorder and undesirable states in processes [21]. While these studies are a valuable base, the potential of entropy as a unifying indicator that correlates manufacturing process disorder with productivity, and with zero-defect performance, is yet underdeveloped.

It is important here to note the difference between information entropy and thermodynamic entropy. The difference between thermodynamic entropy and Shannon entropy is that the former represents the statistical behavior and irreversibility of physical systems, while the latter quantifies uncertainty in information given a probability distribution. The present study is based on the latter interpretation. In a sense, the process entropy is an information-theoretic measure of uncertainty in the states of the manufacturing process that are observed. A higher entropy value implies the more dispersed or unpredictable the state of the process is with respect to the relevant outcomes, while a lower value implies the more concentrated and predictable the process state is with respect to the outcomes. This interpretation establishes the quantitative connection between the Six Sigma perspective of statistical-variation, the Lean perspective of waste-reduction and the ZDM perspective of defect-prevention, while it does not claim that information entropy is the same as thermodynamic entropy.

Proposed perspective is also in line with the evolution of manufacturing improvement, which is increasingly integrated systems. The focus of lean methods is to make things move and stop non-value adding activities, Six Sigma is about reducing variation and defects; whereas ZDM is about preventing defects in the first place. Green Lean Six Sigma takes these goals one step further by incorporating resource and environmental performance [8, 20] and smart manufacturing adds continuous digital sensing, analytics and feedback [3, 4, 11]. Entropy may be a layer common to all of these methods since it can measure the uncertainty of process outcomes, and allow for systematic investigation of whether process disorder reduction is correlated with productivity improvement. Therefore, this study suggests an entropy-based framework to analyze the relationship between manufacturing process disorder and productivity in Lean Six Sigma and Zero-Defect Manufacturing environment. The study does not consider entropy just as another optimization method, but as a possible system-level indicator, process uncertainty can be quantified in terms of entropy and linked to system operational performance. The model also investigates the possible effect of the maturity of Lean Six Sigma implementation on the relationship between process entropy and manufacturing performance. This helps to go beyond the traditional question of whether LSS leads to good performance to a more specific one: whether the elimination of measurable process disorder is correlated with increased manufacturing productivity and whether a mature LSS system enhances this correlation.

The study, therefore, focuses on three related research needs: (i) to develop a theoretically grounded representation of manufacturing process disorder based on information entropy; (ii) to empirically examine the relationship between information entropy of manufacturing processes and manufacturing productivity; and (iii) to assess Lean Six Sigma maturity as a potential conditioning mechanism in this relationship. The proposed approach aims to integrate information-theoretic measurement with the existing philosophies of manufacturing improvement to offer a more holistic base for assessing productivity, variation and defect performance in modern manufacturing system.

The rest of this paper is organized as follows. The literature review in Section II covers Lean Six Sigma, Zero Defect Manufacturing, entropy and its uses in modern manufacturing. The research questions are given in Section III.

Theory and conceptual relationships are developed in Section IV. The proposed regression methodology is outlined in Section V. The testable propositions are given in Section VI. Theoretical and managerial implications, limitations and conclusions are discussed in Sections VII – IX respectively.

2. LITERATURE REVIEW

A. Lean Six Sigma: Foundations and Integration

Lean manufacturing is based in the Toyota Production System and is basically about creating value for customers by systematically eliminating non-value-adding activities. It focuses on identifying values, value stream mapping, Continuous flow, pull based production and Continuous Improvement. Overproduction, waiting, transportation, over-processing, inventory, unnecessary motion, and defects are the main types of waste. Lean aims to minimize these wastes, thereby increase the process flow, shorten cycle and lead times, capacity utilization, and operating costs [14], [16], [19]. The success of the Lean, however, is highly dependent on the selection of the right tools, adequate process information, employee engagement, and organizational readiness. Comparative study of Lean and Six Sigma implementation shows that there are no similar critical success factors for the two approaches. The implementation of Lean is more influenced by employee involvement and organizational culture, while technical skills and expertise play more important roles in Six Sigma [17]. This is significant because "productivity improvement" does not necessarily result from the use of a particular Lean tool, but also relies on the organizational capacity to retain process change.

Six Sigma is an approach to process variation reduction and defect prevention that is complementary to Lean. Typically, the methodology is carried out using Define–Measure–Analyze–Improve–Control (DMAIC) which offers a structured approach to the identification of root causes, the analysis of process performance, process improvement, and the maintenance of control. Unlike traditional Lean approaches Six Sigma focuses more on statistical analysis of processes, process capability, and quantitative performance measurement. The goal is usually interpreted to mean a level of process performance that equals about 3.4 Defects Per Million Opportunities (DPMO) according to the traditional Six Sigma assumption.

The combination of Lean and Six Sigma overcomes the drawbacks of using either one approach or the other. Lean focuses on improving the process flow and eliminating non-value adding activities, while Six Sigma is concerned with decreasing the variation in the value adding processes. There are two approaches, one complementary to the other; excessive variation can create defects, rework, scrap, waiting and other wastes [15] and [16] and [24]. This process of lean thinking combined with statistical process improvement resulted in a Lean Six Sigma (LSS) framework that has been used in manufacturing and other organizational contexts [16] and [18]. The literature also shows that LSS can be used for system level performance management beyond just isolated process improvements. Productivity, quality, cycle time and operational efficiency are some of the benefits that have been linked to integrated LSS approaches [15]–[19]. For instance, Roth et al. [25] created a framework of system excellence that integrates lean thinking, business excellence and factory physics, and shows the potential of including variability, lead time, productivity and failure-related costs in a more comprehensive performance-assessment structure. Likewise, Sreeram and Thondiyath [24] showed that using Lean and Six Sigma in combination with a systems-engineering approach can enhance system visibility and facilitate continuous improvement. Recent studies also suggest that LSS is gradually becoming combined with digital and sustainability related manufacturing paradigm. Green Lean Six Sigma (GLSS) integrates waste reduction, quality improvement and environmental considerations, and digital technologies and strategic alignment have been identified as critical enablers in recent reviews [20]. Previous research also showed how to apply Lean, Six Sigma and entropy-based techniques to prioritizing sustainability-focused improvement options [8, 9]. The evolution of LSS from a body of process-improvement tools to a more comprehensive framework for the integration of operational, environment and technology goals is evident in these developments.

B. Zero Defect Manufacturing and the Shift Toward Prevention

The concept of Zero-Defect Manufacturing (ZDM) takes the traditional quality management concept one step further by switching from identifying nonconforming product to preventing defect formation during manufacturing. Current ZDM research has classified defect prevention and defect compensation as complementary approaches for the goal of ZDM [5]. ZDM does not see quality as a product quality assessment at the end of the production process but rather as a quality as a property that is integrated into the whole range of the production process. In the era of Industry 4.0, technology has greatly broadened the technological foundation for ZDM. Manufacturing systems can detect when conditions are abnormal and take corrective action before it produces nonconforming output by using sensors, industrial connectivity, AI, predictive analytics and real-time process monitoring [6]. As a result, ZDM has been increasingly seen as a closed loop quality paradigm where information is continually gathered, analysed and used for corrective or preventative action.

This change is more significant for LSS since both share the idea of dealing with sources of instability in the process, but with different angles. With Six Sigma, you're looking to statistically minimize the variation; with ZDM, you're looking to not allow variation to become a defect. Lean contributes by eliminating process waste and any unnecessary sources of instability. This means, ZDM is not a quality philosophy in itself, but it is a complement to LSS. Recent studies in human-centric ZDM also point out that human expertise, organization and worker-worker and worker-technology interaction are important factors for defect prevention with increasingly automated production technologies. Manufacturing systems are also getting more complex with the transition to Industry 4.0 and Industry 5.0. Information is created in multiple machines, operators, materials, processes, and digital systems, and this has the potential to create better control opportunities but also new sources of uncertainty. Wang et al. [22] show how technology of Industry 4.0 can be combined with Lean Six Sigma and value-stream mapping in the context of human-centred design of workstations. In the same way, studies on the manufacturing information field demonstrate that information entropy and fuzzy approaches can be applied to analyse the temporal and spatial characteristics of information in manufacturing system and the relationship between the manufacturing operation and the cognition [1]. The results support the necessity of analytical tools that can capture the uncertainty of the processes for elements of the manufacturing system that are interconnected.

C. Entropy as a Manufacturing Construct

Entropy offers a possible numerical base to evaluate unpredictability and chaos in manufacturing systems. Two interpretations stand out in this regard. One is thermodynamic entropy that informs about statistics and irreversibility of some physical systems. The other is Shannon entropy which assesses unpredictability accompanying certain probability distributions. This research takes into account the information-theoretic interpretation and therefore refers to entropy of processes as a measure of unpredictability of observable states of manufacturing process.

For a discrete probability distribution, Shannon entropy can be expressed as shown in Fig. 2:

$$H(X) = - \sum_{i=1}^n p_i \log p_i$$

Where:

- $H(X)$ = entropy of the process
- p_i = probability of the i -th outcome
- n = total number of possible outcomes

Interpretation:

Entropy quantifies the uncertainty or disorder in a distribution. Higher values indicate greater unpredictability, while lower values indicate a more predictable system.

Fig. 2. Shannon entropy formulation used to represent process entropy, with definitions of terms and interpretation of high versus low entropy values.

where p_{i_i} is the probability of the occurrence of process state i_i . The smaller the entropy value, the more observations fall into a few states, and the larger the entropy value, the more the observations are spread out across the possible states. In manufacturing, the states can be defects, cycle-time variations, machine states, quality results, or other observed process states. Entropy can thus be used to transform state information about processes in different states into a common quantitative representation.

“There's a lot of work that's been done by industry that shows that entropy can be used outside of the theory,” he said. Kaswan and Rathi [9] applied entropy-based weighting in the TOPSIS for the prioritization of sustainable manufacturing method, and Singh et al. [10] integrated entropy-based criteria weighting in the hybrid decision making for Lean Six Sigma project selection. The results of these studies show that the information content or uncertainty of decision criteria can be quantified by entropy, and entropy can be used to assist structured manufacturing decision-making. More directly relevant to the current study, Verma et al. [7] created a value-stream mapping method using entropy to determine the workstation that is responsible for rejections and rework while also taking energy and waste into account. This work delivers evidence of embedding entropy within an LSS orientated manufacturing framework rather than as just an abstract measure of information.

An idea has also been brought to manufacturing complexity and information management, which is called entropy. Herrera-Vidal et al. [11] constructed a systematized configurator to deal with manufacturing complexity integrating the Lean Production and Industry 4.0 concepts, dividing the complexity into static and dynamic versions. In the same way, Kong et al. [1] set up an information-field analysis model based on the information entropy and fuzzy mathematics, and analyzed the information and cognitive load of operators in manufacturing systems. These analyses show that the concept of entropy-based "measures" can reflect features of manufacturing systems that are not directly captured by conventional performance measures. There is an additional conceptual basis by the theory of entropy for process science developed by Meyer et al. [21]. They consider process entropy as misalignment and disorder in transformation processes. Improvements and innovation can decrease disorder because they produce better alignments between the resources and the requirements of the process, while a change in inputs and disruption of system components can increase disorder [21]. This viewpoint is especially applicable to LSS, and is a systematic process of eliminating unwanted process states and bringing the process back into alignment, which can be equated with continuous improvement. However, the literature has generally used entropy on specific problems dealing with decisions, complexity, information or workstations. The relationship between the manufacturing process entropy measure (specified in a systematically empirical manner) and the productivity results and LSS maturity is not sufficiently developed. This is a significant step toward scaling up entropy from an analytical tool to a performance metric to be used in a manufacturing process.

D. Productivity, Quality, and the OEE Nexus

The aim of Lean and Six Sigma is to improve productivity and is often shown through metrics such as throughput, cycle time, productivity of the workforce, equipment effectiveness, costs, and quality level. Lean enhances productivity at the expense of boosting flow and eliminating non-value adding activities. In contrast, Six Sigma increases productivity thanks to reduction in variance and defects. Use of Lean has resulted in shorter production and setting-up times, better usage of capabilities, higher delivery efficiency, improved quality, and higher customer satisfaction. Overall Equipment Effectiveness (OEE) is a performance metric that suits well the proposed entropy-based concept since it embraces three aspects of equipment performance: availability, performance, and quality. Consequently, OEE is therefore expressed as shown in Fig. 3:

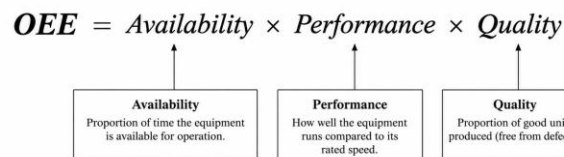


Fig. 3. Decomposition of Overall Equipment Effectiveness (OEE) into its availability, performance, and quality components.

The quality component directly affects defective and reworked output, availability and performance reflect losses due to downtime, operating speed decreases, and interruptions of the process. OEE thus represents a

representative value for various operational losses that can occur because of the process being unstable or disordered. This connection between process variability and productivity is also reinforced by the general literature relating to LSS studies. Too much variation can cause defects, rework, scrap, waiting, equipment loss or extra processing needs, which are all factors in reducing effective production capacity. Many of these losses can be addressed by leveraging lean tools, and six Sigma tools look to uncover and eliminate the statistical causes of these losses [15, 18]. Variability and reduction in lead-time can also be linked to bottom-line effects like productivity and failure costs as shown in system level performance research [25].

The relevance of these composite measures is reinforced by the spread of production systems that generate increasingly large quantities of diverse information in the industry 4.0 environment. The use of digital technologies can enhance monitoring and responsiveness, but can also increase the number and dependency of observable process states [1], [11]. Thus, a measure of productivity like OEE can be used to produce an outcome variable of which the operational consequences of a process uncertainty can be measured. The literature, however, is not adequate to conclude whether an information-theoretic measure of process entropy statistically accounts for the variation in OEE or labour-hour productivity. In most existing studies, entropy is used to make decisions or assess the complexity of the process or to analyze the process at the local level [1], [7], [9]–[12] and is not used to test it as an explanatory variable for manufacturing productivity. This distinction is at the heart of this contribution of this study.

E. Research Questions

RQ1: Does manufacturing process entropy negatively influence Overall Equipment Effectiveness (OEE) and labour-hour productivity in plants operating under Lean Six Sigma programs?

RQ2: Does Lean Six Sigma implementation maturity moderate the relationship between process entropy and manufacturing productivity outcomes?

RQ3: Does Zero Defects orientation mediate the relationship between process entropy reduction and productivity performance in Lean Six Sigma-driven manufacturing systems?

F. Synthesis and Research Gap

The literature examined reveals the three complementary streams. First, Lean Six Sigma gives us a framework for operational-excellence that includes elimination of waste and statistical variation reduction [14]–[18], [24]. Second, Zero Defect Manufacturing adopts quality management to continuous defect prevention and more and more integrates digital and human-centric capabilities [5], [6], [23]. Third, the entropy-based approaches offer quantitative representations of manufacturing uncertainty, manufacturing complexity, manufacturing information distribution, and manufacturing process disorder [1],[7], [9-12],[21]. While there has been significant development in each stream, there is not much integration between the two streams. In general, existing LSS research has concentrated on the more traditional measures of productivity, and the ZDM research has centred on preventive measures for faults, fault compensators, and technologizing. The research in manufacturing has mainly been focused on local process conditions, decision making, information complexity or prioritizing sustainability. Therefore, little empirical information is available to answer the question of whether process entropy can serve as a system-level predictor of manufacturing productivity in LSS environments.

A second gap relates to the level of LSS maturity. According to previous studies, among the factors that impact the success of Lean and Six Sigma implementation are leadership, skills, employee involvement, organizational culture, training, project selection [17, 18]. LSS maturity, however, is typically studied as a characteristic of implementation or as a success factor rather than as a moderating factor which would alter the strength of the relationship between process uncertainty and productivity. A mature LSS system can be anticipated to limit process-state variability, using the tools of standardized work, statistical control, root cause analysis, continuous improvement and disciplined corrective action. Therefore, the same amount of uncertainty in the underlying process could result in different productivity implications based on the level of LSS maturity. A third lacuna relates to the integration of Zero-Defect Manufacturing in this relationship. The focus of ZDM is on defect prevention from its root causes [5] and

human-centric ZDM is based on technology and organizational factors [23]. Empirical approaches that relate process entropy with LSS maturity, ZDM orientation and productivity, however, are still underdeveloped.

The present study, therefore, builds on previous research by conceptualizing process entropy as an information-theoretic measure of manufacturing process disorder, analyzing their relationship with OEE and labour-hour productivity, and situating LSS maturity as a moderating variable. Zero Defects orientation is also added in to explore if robust orientation on defect prevention is a pathway through which process disorder is reduced, leading to improved productivity. This integrated view transcends the separate consideration of Lean, Six Sigma, ZDM, and entropy as improvement tools, and it considers how they work together in the same productivity-oriented environment.

3. RESEARCH METHODOLOGY

A. Research Design

The research method of this study is of quantitative, cross-sectional type which uses variance-based structural equation modelling. The authors used PLS instead of covariance-based SEM for three reasons. First, the research is directional and exploratory, while the entropy-based models of manufacturing disorder have not been explored in the Lean Six Sigma literature yet. Second, the model includes latent variables involving multi-item reflective measures regarding a moderate-size sample. The last reason for using PLS is that this method does not require assumption of any distribution for the indicators used, which is needed for Likert-type perceptions data obtained from employees in the company. Everything was computed using SmartPLS 4 (ver. 4.1.1.8).

B. Instrument Development

The structured survey was created and delivered through an online platform. In the first section, the demographic and organisational profiles of the participants were analysed through the use of ten queries, including age, sex, education level, job title, time spent in industry, type of organisation the respondent is working at, corporation size, existence of a Lean Six Sigma initiative, length of time an organisation has been implementing Lean Six Sigma, and role in the analysis of industrial data. The latter two aspects work as screening variables, verifying that survey responses are collected only from people with either direct contact with productivity data in a Lean Six Sigma organisation or those taking part in its evaluation.

The constructs that made part of Section B were included as substantive constructs. A total of fifteen reflective indicators were equally allocated to three latent variables, where the indicators 1 to 5 represent Process Entropy, the indicators 6 to 10 represent Manufacturing Productivity, and the indicators 11 to 15 represent Zero Defects Orientation. All the substantive indicators were measured through five-point Likert scale. The operationalisation of the various constructs made is presented in the table I.

TABLE I CONSTRUCT OPERATIONALIZATION AND INDICATOR ASSIGNMENT

Construct	Code	Indicators	Nature	Role in model
Process Entropy	PE (R1)	1–5	Reflective	Exogenous
Manufacturing Productivity	MP (R2)	6–10	Reflective	Endogenous
Zero Defects Orientation	ZDO (R3)	11–15	Reflective	Endogenous
LSS Maturity	LSSM	To be added	Reflective	Moderator (not yet specified)

Note: Full item wordings to be inserted in the Appendix prior to submission.

C. Sampling and Data Collection

The individuals participating in the study consisted of people working in manufacturing and operations, specifically in the automotive industry, electronics, process and chemical industry, and heavy engineering sector. The researchers used purposeful sampling and involved people whose job it is to control or monitor production efficiency and production cost figures.

D. Analytical Procedure

The analysis followed the two-stage protocol of PLS-SEM. In the first stage, the measurement model was evaluated. In this stage, the reliability of the indicators was measured through outer loadings, the reliability of internal consistency was measured through Cronbach's alpha, rho_A and composite reliability, the convergent validity was measured through average variance extracted and the discriminant validity was measured through the criteria of Fornell-Larcker and heterotrait-monotrait ratio of correlations. It is only when the criteria for the measurement model have all been met that the results of the structural model are interpreted. In this second phase, the structural model was evaluated on the basis of measuring the path coefficients, coefficient of determination, effect size, and predictive relevance and the significance of the results is checked through bootstrapping with 5,000 subsamples.

The resulting analytical framework is illustrated in Fig. 4.

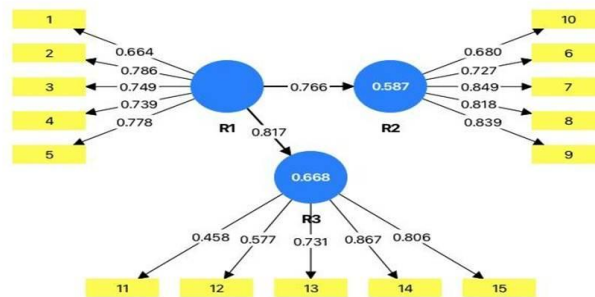


Fig. 4. PLS-SEM framework for the Lean Six Sigma entropy model..

Yellow rectangles are your measured variables. Each one is a single survey item, numbered 1 to 15. These are the things respondents actually answered.

Blue circles are your latent constructs. These aren't measured directly. R1, R2 and R3 exist only as statistical estimates inferred from the yellow boxes attached to them: items 1–5 form R1, items 6–10 form R2, and items 11–15 form R3.

The two kinds of arrows mean different things.

In connecting arrows from blue circle to yellow rectangles lies the measurement model. The arrows indicate that the construct leads to responses thus qualifying these as reflective indicators. The numbers represented here refer to outer loadings: outer loadings range from .664 to .786 for R1, from .680 to .849 for R2, and from .458 to .867 for R3. Therefore, it is possible to see the problem related to item 11, which is located at .458 compared to item 14 which has the loading of 0.867. Arrows connecting blue circles refer to structural model. Here, the figures represent path coefficients. Total of two path coefficients exist: R1 to R2 equals 0.766 and R1 to R3 equals 0.817.

4. RESULTS

A. Measurement Model: Indicator Reliability

The outer loadings for the fifteen indicators are presented in Table II. The loadings of the variable "process entropy" are between 0.664 and 0.786 while the loadings of the variable "manufacturing productivity" range from 0.680 to 0.849 with all indicators above the exploratory research threshold of 0.60. The construct "zero defects

orientation" however has a higher range of results as indicators number 13, 14 and 15 are loaded too strongly at 0.731, 0.867 and 0.806 respectively with indicators 11 and 12 being loaded rather weakly at 0.458 and 0.577.

TABLE II OUTER LOADINGS

Indicator	PE (R1)	MP (R2)	ZDO (R3)
1	0.664	—	—
2	0.786	—	—
3	0.749	—	—
4	0.739	—	—
5	0.778	—	—
6	—	0.727	—
7	—	0.849	—
8	—	0.818	—
9	—	0.839	—
10	—	0.680	—
11	—	—	0.458
12	—	—	0.577
13	—	—	0.731
14	—	—	0.867
15	—	—	0.806

B. Internal Consistency and Convergent Validity

Construct reliability and validity are reported in table III. For the variables of PE, MP and ZDO, the values of Cronbach's alpha are respectively 0.799, 0.844 and 0.740 which are above the minimum threshold of 0.70 while the values of composite reliability for the three variables respectively are 0.861, 0.889 and 0.824 which show that the constructs are internally consistent. The convergent validity is confirmed only for the constructs of PE and MP with their AVE being 0.554 and 0.617 respectively. The AVE for ZDO is marginally less than the limit of 0.50 which can be due to poor values of factor loading for indicator 11 and 12.

TABLE III CONSTRUCT RELIABILITY AND VALIDITY

Construct	Cronbach's α	rho_A	CR (rho_c)	AVE
PE (R1)	0.799	0.806	0.861	0.554
MP (R2)	0.844	0.860	0.889	0.617
ZDO (R3)	0.740	0.808	0.824	0.496

C. Discriminant Validity

Discriminant validity was assessed using both the Fornell-Larcker criterion (Table IV) and the heterotrait-monotrait ratio (Table V), with the latent variable correlation matrix reported in Table VI for reference. Under the Fornell-Larcker criterion the square root of the AVE for ZDO is 0.704, which is lower than its correlation with PE of 0.817. The criterion is therefore not satisfied for the PE–ZDO pair. The HTMT results confirm this: the ratio between ZDO and PE is 1.010, exceeding both the liberal 0.90 and the conservative 0.85 thresholds, and indicating that the

two constructs are not empirically distinguishable in the present measurement instrument. The PE–MP ratio of 0.910 also exceeds the conservative threshold, while the MP–ZDO ratio of 0.852 is marginal.

TABLE IV DISCRIMINANT VALIDITY — FORNELL-LARCKER CRITERION

Construct	PE (R1)	MP (R2)	ZDO (R3)
PE (R1)	0.744		
MP (R2)	0.766	0.786	
ZDO (R3)	0.817	0.704	0.704

Diagonal values (bold in original output) are the square roots of AVE; off-diagonal values are latent variable correlations.

TABLE V DISCRIMINANT VALIDITY — HETEROTRAIT-MONOTRAIT RATIO (HTMT)

Construct	PE (R1)	MP (R2)	ZDO (R3)
PE (R1)			
MP (R2)	0.910		
ZDO (R3)	1.010	0.852	

TABLE VI LATENT VARIABLE CORRELATIONS

Construct	PE (R1)	MP (R2)	ZDO (R3)
PE (R1)	1.000	0.766	0.817
MP (R2)	0.766	1.000	0.704
ZDO (R3)	0.817	0.704	1.000

D. Structural Model

The structural model as estimated contains two direct paths originating from Process Entropy. Table VII reports the explanatory power of the model, Table VIII the effect sizes, and Table IX the path coefficients. The model accounts for 58.7% of the variance in Manufacturing Productivity and 66.8% of the variance in Zero Defects Orientation, with adjusted values of 0.583 and 0.665 indicating that the explanatory power is not inflated by model complexity. Both effect sizes are substantial by conventional benchmarks, at 1.423 for the PE to MP relationship and 2.012 for the PE to ZDO relationship.

TABLE VII COEFFICIENT OF DETERMINATION (R^2)

Endogenous construct	R^2	R^2 adjusted	Interpretation
MP (R2)	0.587	0.583	Moderate to substantial
ZDO (R3)	0.668	0.665	Substantial

TABLE VIII EFFECT SIZE (F^2)

Relationship	f^2	Interpretation
PE → MP	1.423	Large
PE → ZDO	2.012	Large

E. Hypothesis Assessment

Table IX summarises the status of each hypothesis against the model as currently estimated. Two observations require explicit statement. First, the estimated PE to MP coefficient is positive ($\beta = 0.766$), whereas H1 predicts a negative association. Second, the estimated model contains neither a moderating construct nor a sequential mediation path, so H2 and H3 cannot be evaluated on the present output. These are specification issues rather than evidence against the hypotheses.

Table IX summarizes hypothesis status.

TABLE IX HYPOTHESIS ASSESSMENT STATUS

Hyp.	Statement	Model evidence	Status
H1	PE is negatively associated with MP	$\beta = +0.766$; $f^2 = 1.423$	Direction inconsistent — scale polarity to be verified
H2	LSSM moderates the PE → MP relationship	No moderator in estimated model	Not tested
H3	ZDO mediates the PE → MP relationship	No sequential path; indirect effect not estimable	Not tested

5. DISCUSSION

The findings clearly indicate that there is a strong systematic relationship between the entropy construct and both productivity and zero-defects result. Since 58.7% and 66.8% of the variance of the two endogenous constructs is accounted for, and the effect sizes are clearly greater than those usually required, the entropy construct can be considered as a valid model of the variance in the model variables important for manufacturing performance achievement. The affirmation of the positive sign on the PE to MP path should not be disregarded and should be carefully interpreted. Entropy indicators are expressed in terms of process control, i.e. statements claiming that the process under monitoring is well controlled or that the timings for the changeover are determined and standardized. With such wording, having higher scores means having lower entropy and a positive sign in terms of productivity is what the theory predicts. Consequently, the five entropy indicators should be verified against the type of wording used in the items before making any interpretation concerning the direction of H1. In other words, if a control wording type is used, then the scoring of the indicators should be reversed before reiterating the estimation.

The most important finding about measurement is found in the results on its discriminant validity. An HTMT ratio of 1.010 for Process Entropy and Zero Defects Orientation indicates that the participants failed to distinguish between these two constructs. This is understandable in terms of theory because for organisations that operate well-established Lean Six Sigma systems, the approaches of achieving zero defects and reducing process variance can look like two sides of one coin. In practical terms, this means that the two groups of measuring instruments should not be used together in this project. Consequently, it is impossible to test hypothesis H3, which describes ZDO as a mediator for PE and MP, since a mediator that cannot distinguish itself from its antecedent does not provide any useful information. The marginal AVE for Zero Defects Orientation supports this interpretation. Indicators 11 and 12, which load at 0.458 and 0.577, respectively, are the main reasons for the shortfall. Eliminating these two indicators would increase the AVE of the construct beyond 0.50 but elimination alone will not solve the discriminant validity problem of the indicators being conceptually similar rather than weak in terms of measurement.

6. CONCLUSION

Manufacturing process disorder in this case is defined in the way that it can be used as an entropy measure and its relationship with productivity and zero-defect focus of Lean Six Sigma processes is analyzed in the research through PLS-SEM techniques. The measurement session was sufficient in terms of internal consistency relating to all three concepts and showed well-defined convergent validity for Process Entropy and Manufacturing Productivity

concepts. The structural model was at par, showing that it is able to explain 58.7% of the variance of manufacturing productivity and 66.8% of zero-defect orientation, thus producing very big effect sizes on respective paths. At the same time, the research identifies two constraints of the particular specification and reports them in this paper instead of postponing. First of all, the sufficient discriminant validity between Process Entropy and Zero Defects Orientation was not demonstrated and the model as specified lacks both moderating and mediating elements necessary for the testing of second and third hypotheses. Thus, though the entropy variable has been identified as a solid predictor of manufacturing performance results, there are still questions regarding the influence of Lean Six Sigma maturity and zero-defect orientation on the research findings.

7. LIMITATIONS AND FUTURE SCOPE

The current findings come with four constraints. First, the cross-sectional design prevents causal conclusions to be made; the highlighted findings are only associational. Second, the data are subjective and self-reported, thus eliminating common method bias would require the use of a marker variable or Harman's single factor test. Third, the entropy measure is based on the subjective perceptions of managers rather than objective process data, such as cycle time change or frequency of changeovers. Fourth, discriminative validity was not established for two of the three constructs, which has restrictions on the understanding of relationships at the level of constructs.

The next 5 directions follow easily. First, the entropy indicators need to be rewritten to give more focus to the conceptual distinction between zero-defects orientation and the focus on variability and disorder in process state, and the revised instrument re-validated. Second, the four reflective constructs should also be introduced as a new term - Lean Six Sigma Maturity and its indicator set - and the $PE \times LSSM$ interaction term specified using the two-stage approach so that the moderation hypothesis can be tested. Third, the structural model should be respecified as $PE \rightarrow ZDO \rightarrow MP$ with the direct model of $PE \rightarrow MP$ left in, then indirect effects will be estimated and formal testing of mediation will be possible. Fourthly, bootstrap analyses with 5,000 subsamples are recommended to determine the statistical significance of all path coefficients as well as for out-of-sample predictive relevance assessment using PLSpredict. Fifth, future studies should be done using objective plant information as well as perceptual data, and this should validate the entropy construct against reality, not just perception. A longitudinal extension of the study of the same plants at each of the successive levels of Lean Six Sigma maturity would further enable causal statements that the current design does not support and would enable the trajectory of entropy reduction to be measured, not just inferred.

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