**REPUBLIC OF TURKEY**
**SAKARYA UNIVERSITY**
**GRADUATE SCHOOL OF BUSINESS**

# INTERNAL LEAN MANUFACTURING PRACTICES AND OPERATIONAL PERFORMANCE: A META ANALYSIS APPROACH

## MASTER'S THESIS

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# ACRONYMS AND ABBREVIATIONS

| | |
|---|---|
| **ILMP** | **:** Internal Lean Manufacturing Practices |
| **LM** | **:** Lean Manufacturing |
| **LPs** | **:** Lean practices |
| **OP** | **:** Operational performance |
| **FP** | **:** Firm Performance |
| **TPS** | **:** Toyota Production System |
| **TQM** | **:** Total Quality Management |
| **TPM** | **:** Total Productive Maintenance |
| **SPC** | **:** Statistical Process Control |
| **HRM** | **:** Human Resource Management |
| **JIT** | **:** Just in Time |
| **VSM** | **:** Value Stream Mapping |
| **MTB** | **:** Mean Time Between Failures |
| **MTTR** | **:** Mean Time To Failure |
| **IMF** | **:** International Monetary Fund |

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**Title of thesis:** Internal Lean Manufacturing Practices and Operational Performance: A Meta-analysis Approach

**Author:** Ashiraf Kategaya **Supervisor:** Prof. Dr. Mustafa Cahit Ungan

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Among the major aims of any firm is to keep costs as low as possible. This has become even more critical during the COVID-19 era, where many businesses have been forced to operate below their stated capacity while others have closed shop.

However, even before the pandemic struck, firms both domestic and multinational were already reeling from the cut-throat competition exacerbated by globalization, disruptive technologies, and heightened demand for cheap products and services with increasingly innovative features. To win and sustain such demand, fend off the competition and achieve efficiency with increased value, firms were already trying to streamline their operations using different production techniques, including the lean manufacturing strategy, albeit with mixed results

Therefore, the debate on the efficacy of the ILMPs on OP continues to be a subject of substantial scholarly and practical interest. A substantial amount of theoretical and empirical literature on the relationship has been and continues to be investigated as a result of this. This accumulation of empirical evidence on the ILMP-OP association has gained traction that makes it necessary to carry out another synthesis of findings through a meta-analytic study. However, despite the great strides made in bridging the numerous disagreements in the ILMP-OP relationship, the literature still has significant gaps and discrepancies. For example, empirical evidence on the association is frequently varied, and theoretical debates have remained unexplained in general.

This study aims to narrow the inconsistencies and gaps observed and obtain a clearer picture of the relationship between ILMP and OP. The ILMPs were derived from a proposed model by Shah and Ward (2003). They include statistical process control, total preventive maintenance, continuous flow production, employee involvement, setup time reduction, and pull production. OP as the dependent variable for the study was measured in terms of speedy delivery of materials, flexibility, high productivity, reduction in defects, high first-pass yield, reduced lead time, lower manufacturing costs, high product quality, and waste minimization.

The study comprises 7,075 firms spread across the world and thirty studies published between 2010 and 2020.

The meta-analysis results show a strong positive and significant association between aggregate ILMP and OP, and the same for all the individual practices and OP.

**Key words**: Internal lean manufacturing, Operations performance, Meta-analysis, Moderator

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| **Tez Başlığ:** İç yalın üretim uygulamaları ve operasyonel performans: Meta-analiz yaklaşımı | |
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Herhangi bir firmanın temel amaçları arasında maliyetleri mümkün olduğunca düşük tutmak vardır ve bu, birçok işletmenin belirtilen kapasitelerinin altında çalışmaya zorlandığı ve diğerlerinin faaliyetlerine son verdiği COVID-19 döneminde daha da kritik hale gelmiştir.

Pandemiden önce de ulusal ve uluslararası firmalar, küreselleşme, yıkıcı teknolojiler ve giderek daha yenilikçi özelliklere sahip ucuz ürün ve hizmetlere yönelik artan talebin şiddetlendirdiği rekabet karşısında zorlanmaktaydılar. Bu talebi kazanmak ve sürdürmek, rekabeti savuşturmak ve artan değerle verimlilik elde etmek için firmalar, yalın üretim stratejisi de dahil olmak üzere farklı üretim tekniklerini kullanarak operasyonlarını düzene sokmaya çalışıyorlardı.

Bu nedenle, içsel yalın üretim uygulamalarının operasyonel performans üzerindeki etkisine ilişkin tartışma, önemli bir bilimsel ve pratik ilgi konusu olmaya devam etmektedir. Bu konuda önemli miktarda teorik ve ampirik çalışma yapıldı ve yapılmaya devam ediyor. Ancak yapılan çalışmalarda tutarsız sonuçlar elde edilmekte olması bir meta analiz yapılmasını gerekli kılmıştır.

Bu çalışma, gözlemlenen tutarsızlıkları ve dolayısıyla içsel yalın üretim uygulamaları ile operasyonel performans arasındaki ilişkinin daha net bir resmini elde etmeyi amaçlamaktadır. Çalışmada kullanlan içsel yalın üretim uygulamaları Shah ve Ward (2003) tarafından önerilen bir modelden elde edilmiş olup istatistiksel süreç kontrolü, toplam önleyici bakım, sürekli akış, çalışan katılımı, kurulum süresinin azaltılması ve çekme üretimi içermektedir. Çalışmanın bağımlı değişkeni olan operasyonel performans ise malzemelerin hızlı teslimatı, üretim esnekliği, artan üretkenlik, hata oranlarında azalma, ilk geçiş verimi, azaltılmış teslim süresi, daha düşük üretim maliyetleri, yüksek ürün kalitesi ve atık minimizasyonu açısından ölçülmüştür.

Çalışmada dünya çapında 2010-2020 yılları arasında yayılmış 30 makaledeki 7.075 firma örnek hacmi olarak kullanmıştır.

Meta analiz sonuçları bir bütün olarak içsel yalın uygulamalar ve bireysel uygulamalar ile operasyonel performans arasında güçlü bir pozitif ve anlamlı ilişki olduğunu göstermiştir.

**Anahtar kelimeler:** Dahili yalın üretim, Operasyon performansı, Meta-analiz, Moderatör

# INTRODUCTION

With firms focused on how to increase productivity and competitive growth while making use of minimal manpower, raw materials, energy, machinery, and other input, a major feature is the identification and analysis of practices that will help achieve this. Evidence of the literature on lean manufacturing suggests that the internally related constructs of lean manufacturing (ILMPs) have aided industrial companies in improving their internal processes. However, for clarity, the real effect of these practices or principles under the specific ILM and the general lean manufacturing on the contemporary measures of operational performance, i.e., flexibility, manufacturing cost, dependability, speedy delivery of products, the quality of the final products, etc., have varied from one implementer to another or researcher to another.

In the 1950s, Toyota Motor Company's Taiichi Ohno created the lean strategy (Ohno, 1988). It was a business concept that centered on systematically identifying and eliminating waste from a process, as well as modifying and enhancing processes while delivering quality products and greater value to customers at the same or even less cost. (Motwani, 2003; Ohno, 1988).

A lean production strategy generates improved levels of quality and productivity, as well as better customer responsiveness, according to several studies (Chavez et al. 2013; Ghosh et al. 2013). The effect of the lean strategy is primarily based on empirical research that it improves the competitiveness of a company (Nawanir et al., 2013; Wickramasinghe et al., 2016). It is worth mentioning that the significance of LM as a production strategy is critical not only in production or manufacturing, but also throughout its supply chain. Lean manufacturing in all practical sense looks to be a radical production and innovation methodology that is not only restricted to the original purpose for which it was invented, that is to say the production floor, but also enjoys wide applicability in many other functions of organizations such as management, purchasing, marketing, finance, logistics and human resource (e.g., see Womack et al., 1990). Lean manufacturing is linked to shorter lead times in work-in-process inventories and production, as well as improved supply chain performance and flexibility. (e.g., see Marodin et al 2017). For lean implementation, the intended goal for the organization is the shift in thinking to a whole of organizational cost approach, which disregards the different independent cost structures like warehousing and transportation. Instead, it focuses on the total cost of delivering value to the customer with the least expected cost and waste on the part of the producer (e.g., see Goldsby and Martichenko 2005). This kind of focus lends credence to the argument that it is the managers' shared goal to continually seek for improvement within and between organizational functions or divisions. This structure of activities/processes within (intra) and between (inter) companies is critical for gaining increased profitability and a competitive advantage over the competitors (Lambert et al., 1998).

Just as (Shah and Ward, 2007) aver that the strategy's main goal is to remove waste (muda) by cutting costs, there has been no time that this goal has been sought by nearly every firm as it has been in this COVID-19 pandemic era. The turbulence and uncertainty in almost every function of operations management for businesses, i.e., marketing, sales, production, finance, logistics, and supply chain, communication, human resource, etc., as a result of the pandemic have left businesses scampering to institute the most drastic of austerity and cost-cutting measures to survive. Such drastic measures taken include business organizations downsizing their labor force, redirecting resources to only necessary operations, pulling funds away from R&D, changing and cutting back on their suppliers, trying remote working for the employees, changing production lines to produce items in demand like masks, protective personal equipment (PPE) and medical gowns and many others to remain in operation.

To give a brief background of the impact of the pandemic in real-world: in Turkey, 149,382 businesses temporarily closed their operations in March 2020 within the scope of the measures instituted by the government of Turkey to limit the spread of the corona virus disease (see the T.C Ministry of the Interior gazette, 19.03.2020). However, the businesses that remained operational as a result of a waiver from the Turkey government, particularly those in manufacturing, were faced with operational problems such as shortage of blue and white-collar workers in factories (e.g., see Açıkgöz and Günay, 2020), supply chain disruptions for essential raw materials like chips, increased costs of production (Yildirimli & Öztürk, 2020), and financial constraints like liquidity squeezes and limited access to financing (e.g., see Ercin, 2020) as a consequence of the government employing harsh restrictive measures like lockdowns, border closures and people movement curtailments (see Ongur and Işık, 2020; Yildirimli and Öztürk, 2020). While tourism in Turkey was hit exceptionally, other industrial sectors such as energy, aviation, automotive, textiles, defense industry, electronics, chemicals etc were also not spared (e.g., see Yildirimli & Öztürk, 2020). A case in point is the Turkish automotive industry which had a 15% decline in demand domestically for Turkish-made cars, a 77% decline in the outside markets and an 81% decline particularly to the European Union (T.C Ministry of Commerce; April, 2020). The construction sector which accounted for 5.4% of Turkey's 34 billion dollar national income ground to a near zero percent contraction in 2020, (e.g., see The Swiss Business Hub Turkey (SBHTR) report).

In China, the early closure of factories in Hubei province in Q1 (and the decelerated progress of plants inside Hubei) in the initial days of the pandemic had the greatest impact on the global supply chains that go through China, leading to difficulties in procuring and securing critical parts (see Mckinsey report, "*COVID-19: Implications for businesses*" March 2020).

According to a March 2020 report by Mckinsey global institute, "*COVID-19: Implications for businesses*", to the business operations, production, and supply chain managers, the biggest challenge for them during the pandemic has been the uncertainty in the trends of customer demand. That is to say, instances of customers having pre-ordered consignments not using them, the difficulty of forecasting demand rebound, jostling for prioritization in receiving the products from the factories, etc., all point to an unpredictable environment that manufacturers are working in.

Therefore, such unprecedented disruption nudges practitioners, planners, and researchers to devise production techniques that can help their companies integrate the proposed cost-cutting measures to achieve efficient and effective operations, cut down unnecessary waste, and achieve lower operational costs. At the same time, they ought to strive to achieve these without reneging on the value and quality of services and products offered to the end-users. And to accomplish this, one of the reliable and timeless waste elimination techniques that have been tried and tested in such times has been the lean manufacturing strategy. This strategy has been largely reliable for serious firms seeking a revamp or streamlining of their operations, although sometimes the results of its implementation have been mixed from one implementer or researcher to the other.

However, even before the pandemic struck, because the world had become increasingly globalized. The implication of this on the domestic firms and, to some extent, multinationals was a break out of an intense cut-throat competition exacerbated by disruptive technologies, increasing labor costs, the limited life span of technological and competitive edges, and constant demand for cheap products and services with increasingly innovative features and high quality. And therefore, to win and sustain demand, outsmart the competition and achieve efficiency with increased value, firms were already trying to improve their operations with less resources, capital, labor, time through a wide range of proven lean manufacturing practices. ILM practices have already become popular among manufacturing, production, and operations practitioners and scholars. For instance, firms have used these ILMPs to continuously strive to improve internally to compete in an increasingly globalized economy, and new ILM approaches in the field of operations have arisen in recent decades to this goal (Cua et al., 2006; Fullerton et al., 2014; Fullerton and Wempe, 2009). And although several studies have repeatedly confirmed the positive relationship between ILMP and operational performance., the significance and the degree of impact of the ILMP-operational performance is still not out rightly settled, and inconsistencies still exist.

To cite another concern is that as manufacturing becomes more dynamic as a result of the incorporation of the technologies ranging from automation, artificial intelligence, digitalization to the ever-evolving efficient ways of doing business and operations all over the globe, scholars, and practitioners have mulled going back to the drawing board to attempt to re-evaluate the feasibility of ILMP implementation. Scholars ask at every turn if ILMP is still a viable and relevant tool for achieving improved firm performance and meeting challenges of the day as it were back then. As a result, more theories and techniques resulting from more research are introduced in the LM literature to update it and enable it to meet the challenges of the rapidly changing environment and operations management of business organisations.

As a result of the aforementioned reasons or objectives, scholars around the world have increasingly taken more interest in exploring the effects of the adoption of ILM practices on operational performance (Tortorrella, Miorando, and Marodin 2017).

There are three primary categories of results that explain the relationship between internal lean manufacturing methods and operational performance in the available literature;

(a) a positive and significant association (e.g., Sezen et al. 2012; Yadav et al., 2019);

(b) absence of a significant relationship (e.g., Alcaraz et al., 2014; Bevilacqua t al., 2016); and finally

(c) a relationship that is partly negative but yet significant (e.g., see Marin-Garcia and Bonavia 2015; Bortolotti et al., 2012)

The divergence in the findings above points to the realization that the relationship between ILMP and OP can still be examined or needs further examination. Hence, the need for a comprehensive and quantitative meta-study with clear definitions, measures, and empirical basis to aid in providing a basis for related current and future studies. Identifying and establishing from previous studies which theories are effective in determining the link between ILMPs and the operational excellence of manufacturing firms will be of great help to both practitioners and researchers.

Furthermore, much of the study on the impact of ILM methods on operational performance has been conducted in industrialized countries, including Japan, the United States, the United Kingdom, Germany, Italy, etc. Less attention has been accorded to developing countries, i.e., the lean strategy can be said to be still relatively less known and implemented in developing countries (e.g., see Albliwi, Antony, Arshed, & Ghadge, 2017; AlNajem, Dhakal, Labib, & Bennett, 2013). This study demonstrates that in order to have a clearer view of the impact of LM practices on performance, investigations in the context of all levels of economic development present in the different countries on the globe, whether developing or advanced, are substantially required. Also, the research is among the very few to have specifically targeted the internal aspect of the wider lean manufacturing strategy. It is also the first of its kind to appreciate the impact that different manufacturing types play on the LM-OP association. Most of the studies have taken a blanket description of manufacturing and thereby missing the wide differences in manufacturing types and their eventual impact on the LM-OP. This particular study investigated ILM in the realm of process and discrete manufacturing industries.

The inconsistencies in ILMP- operational performance relationship cited in most of the studies range from definitions, measures, dimensions, concepts to theories. Clarifying and identifying the reasons for these contradictions is one of the aims of this research. This will help in determining and justifying which individual ILM practices and dimensions are best suited for ILMP-OP relationships, reveal new changes in lean manufacturing, thereby contributing to lean manufacturing literature and providing a foundation for future studies.

The study identifies and classifies six ILMPs and the operational performance outcomes. Furthermore, the effects of ILM practices on operational performance dimensions will be evaluated. This provides both practitioners and researchers with insight into the significance and impact of ILMP on operational performance. Determination of the ILM practices that have the most influence on operational performance will greatly assist decision-makers on which key dimensions to take into consideration. It would go a long way in addressing the inconsistencies found in ILMP- operational performance studies or literature.

The study examines the ILM literature by formulating a meta-analytic procedure and executing an empirical synthesis of findings to assess the ILMP-OP relationship and its moderation effects. In conducting a meta-analysis of the ILMP-OP association, the research focuses on the operationalization of ILM to evaluate its construct reliability and validity as a strategic resource component. For the formulation, empirical testing, and application of the strategic resource theory, high construct validity and reliability are essential. In addition, ILM's validity must be strong to assess its relationship with OP. Determining which moderating factors are key to ILMP- operational performance relationship reveals under which conditions the impact is strong or weak. This establishes the conditions under which ILM is most effective. This is in sync with the contingency theory (Lawrence and Losrch, 1967), which holds that organizational performance is determined by the degree to which the organization and the aspects of its environment are congruent. Moreover, Mackelprang et al. (2014) argued that the inconsistencies in empirical results and unanswered questions for both research and practice could be addressed by assessing moderating factors.

This review considers primary empirical studies from 2010 to 2020 from the highly ranked journals and other databases. This period accounts for the most published, rich in substance, up-to-date with the prevailing global situation such as the pandemic and the revised articles on the ILMP- operational performance relationship. It is sufficient enough to provide new insights on the advances made on ILMP-operational performance over the years. For a primary study to be considered empirical, it must meet the criteria for empirical study justified in the methodology section.

A quantitative meta-analysis is adopted to determine the impact of the internal lean manufacturing practices on the operational performance of business organizations. To achieve the objectives, hypotheses as well as contribute to the ILMP- operational performance literature, an all-encompassing approach is adopted.

**Purpose of the study**

Firms and production managers in manufacturing firms incorporate ILM practices to benefit from the numerous operational advantages, such as production costs, productivity, inventory turnover, lead time, on-time delivery, quick delivery, flexibility, quality, space requirements, and so on. Elimination of waste (Muda) in their operations, desire to achieve higher levels of quality and productivity, and creating more value for customers to achieve company competitiveness have led production and operations planners, executors, monitors, and assessors to embrace the phenomenon of ILM. From the different studies carried out, this has been found to bring mixed results. Different ILM practices are found to have varying impacts on the different dimensions of operational performance. Some have been discovered to have a significant and positive impact (Nawanir et al., 2010), others have been found out to have a strong impact if complemented by one or more other ILM practices (Ghosh et al. 2013), and in some instances, no impact has been found with implementing some of the ILMPs with operational performance (Ambra Galeazzo, 2019).

The difficulty to most of the practitioners, however, has been how to measure the overall effect on performance as well as determine the ILM practices that produce results and those that are merely added to complement other practices to achieve stronger and more significant results. The practitioners may also want to know if different and particular situations will affect the outcomes of the association the ILMP-OP differently.

The primary goal of this study is, therefore, to ascertain if there is a positive and substantial link between internal lean manufacturing practices and operational performance through aggregating different quantitative results from different studies done before on this relationship.

For the different outcomes of ILMP-OP in the different situations, practitioners will also get to appreciate the degree at which the proposed relationships are affected or influenced by these third-party situations or variables (moderators), as well as how that can be deployed to their advantage.

**Research objectives**

**Main objective**:

The primary goal for carrying out this research was to determine the extent to which ILM practices impacted manufacturing enterprises' operational performance. By defining the nine operational performance metrics required for achieving improved performance, a meta-analysis is done to help elucidate the relationship between ILMP implementation (in general, and of the six internal lean practices individually) and OP. The goal is to compile all of the empirical evidence accessible to date and provide guidance for future research.

To achieve this, the following objectives have been developed:

• To determine the extent to which aggregate ILMP implementation contributes to the operational performance of manufacturing firms.

• To assess the degree of importance of the individual ILM practices in the improvement of operational performance of companies.

• To explore the effects of potential moderators on the ILMP-operational performance relationship in companies.

**Research Questions**

In line with the main objective and the secondary objectives stated above, this research basing on the formed literature, results, and findings seeks to find answers to the following questions:

a) Is ILMP (as a whole, taking into account any interrelationships between internal lean practices) positively related to operational performance? If that's the case, how strong is the bond?

b) What ILMPs have a stronger impact on operational performance?

c) Is the ILMP-OP relationship homogeneous or heterogeneous? If heterogeneous, to what extent is it influenced by the moderator variables?

**Significance of the study**

In multiple ways, the ILMP-OP study adds to the current lean manufacturing literature and knowledge base by establishing any new theories, concepts, and changes that have evolved in the field of lean manufacturing.

Multinational and domestic firms in this COVID-19 era seek different ways to maximize output and profits while implementing drastic cost-cutting measures that imply using less and less of the inputs or resources. Therefore, firms are looking up for ways to realize a policy of zero waste in their operations. Overproduction, waiting times, wasteful material movement, improper processing, inventory, defects, underutilization of personnel, environmental waste, and underutilization of facilities are all examples of waste that necessitate plant managers devising an ILM strategy. According to Womack et al. (1990, pg. 13), "Lean production is lean because it takes half the raw materials, half the manufacturing space, half the investment in tools, half the human labor in a plant, and half the engineering hours to build a new product in half the time as compared to mass production. Furthermore, it produces fewer defective products, requires significantly less than half of the required inventory at the workstation, and produces a bigger and increasingly diverse array of products."

However, there are contradictions in instances where research has been done, and no positive link has been found between ILMP and OP. This has led to confusion and doubts for the would-be lean strategy adopters (Marin-Garcia and Bonavia 2015).

This study, therefore, comes at an appropriate time to clear up these doubts and inconsistencies by guiding the adopters, planners, and executors of ILM strategy on the latest findings of the impact of ILMP on OP and that it takes time to reap the positive results of implementing ILMP. So is the understanding that results from ILMP will vary in the different settings and conditions that the firm may be in. Such as if the firm is small, medium, or big or if the industry is of processing or discrete manufacturing type. The same will be if the ILMPs have been carried out in an advanced or an emerging market economy country.

Therefore, the study will help plant managers, production planners, operations managers, and supply chain professionals to learn the intricacies of ILMP and how best it can be applied to the maximum benefit in terms of operational excellence in the firm's day-to-day activities

**Scope and limitations of the study**

This research is chiefly focused on ascertaining the link between the implementation of ILM practices on the OP of manufacturing firms. Further, the impact of each of the six constructs of ILMP on OP was also investigated. Through the application of meta-analysis as a study design, the findings of previous studies on the same subject were systematically and quantitatively synthesized to arrive at conclusions about the impact of ILMP on OP. Meta-analysis was used to aggregate the results (inconsistent and contradictory ones included) reported by the main studies in relation to the significance of each of the ILM practices.

Even though it has been heralded as one of the methodologies that give a systematic, generalizable and statistical picture drawn from various studies, meta-analysis design requires exclusion and inclusion criteria when being set up. With this comes different restrictions and limitations, which can bring into question the final findings and conclusions.

Firstly, whereas lean manufacturing is very wide with about 48 practices (Shah and Ward 2007), this study looks at a narrow section of LM with its six internally related lean dimensions. Likewise, only specific dimensions of OP are considered, i.e., quality, flexibility, production costs, speed of delivery, lead times, productivity, first-pass yield, reduction of defects, and waste minimization.

Also, the studies compiled are exclusive to only the period between 2010-2020, which again may have left out a number of important studies outside this time range

Studies looked at are only written in English, which is a limitation in itself from a number of other rich studies authored in other languages.

Because it is a tedious activity that requires maximum care and attention to not miss out on any information or record incorrectly any detail, coding reliability, in this case, can come into question because it was largely done by the researcher. However, for cross-checking purposes, the help of another colleague with better grasp of coding and meta-analysis, in general, was sought to iron out any discrepancies in the results that may have occurred.

This research is also confined to only manufacturing companies, which may bring into question the generalizability as for the case of other types of firms like services, technology, IT, and others.

Last but not least, the study looks into the presence of theoretically identified possible moderators. Investigation of empirical moderators such as time frame, degree of leanness, organizational culture, plant age, unions, etc. that may also moderate the ILMP-OP association have been employed by previous researchers. However, for this particular study, only three factors were chosen to be considered, i.e., “How big or small or medium the size of the industry affects the ILMP-OP association,” “What type of manufacturing firm is the sample and its effect on the ILMP-OP” and finally “In what kind of economy (geographical region) are firms under question operating in and how does this affect the ILMP-OP association?”

**Overview of the research methodology used**

Meta-analysis is the primary research approach used in this study. Through robust methodologies, meta-analyses integrate statistical techniques for aggregating independently reported data (Lipsey & Wilson, 2001). Meta-analyses combine empirical data to produce relevant and practical knowledge that individual research works are often unable to offer on their own (Hunter & Schmidt 1982)

A meta-analysis acts as a statistical analysis tool that gathers and brings together the different results of multiple empirical studies. Meta-analysis is thus carried out by scrutinizing the numerous empirical studies pursuing the same objective, with each of them individually reporting measurements that are not unexpected to have variances or divergences and degrees of error. The purpose of this is to apply statistical techniques to derive a collective estimate that comes close to the undetermined general conclusion based on how this error is discerned.

Meta-analyses, in general, allow for the testing of hypotheses and the synthesizing of bivariate associations by correcting a multitude of errors that can occur, particularly as a result of sampling and measurement errors (Crook et al. 2008; Hunter & Schmidt 2004).

Even so, meta-analysis gives insights into moderator variables that may explain for variances in the relationship of interest, thereby supporting researchers in theory building and testing (Viswesvaran & Ones, 1995). Meta-analyses have a distinct advantage over narrative reviews to assess moderating effects (Aguinis et al., 2011).

Because of the limits of qualitative narrative reviews (see Hunter et al., 1982) and the need for statistical analyses in the synthesis of empirical findings, meta-analyses have gained widespread adoption (e.g., see Glass, 1976). The amount of meta-analytic reviews/studies being done and published in academic journals demonstrates that their use in humanities and social science research is continually gaining traction (see Aguinis et al., 2011).

## Delimitation of the study

The limitations associated with this study aside, the major delimitation is in the number and type of the studies.

A high number of studies and a very large sample size minimizes the presence of Type 1 (false negative) or Type II (false positive) error. For this particular review, a total of thirty studies with a sample size of over 7,000 firms make it firmly possible to minimize or eliminate these errors and to reduce any deviations in the included studies.

Because of the wide-ranging nature of the sample size in terms of the type of economy in which it was adopted, the industry type and the different firm size makes our finding more generalizable and accurate.

## Structure of the thesis

The thesis is divided into four main sections, with the first one presenting the conceptual framework of the research. The problem statement, study purpose, research objectives, research questions, and study significance are all presented in the introduction.

After the introductory part of the thesis, a literature review on lean manufacturing and operational performance is covered in the first chapter.

An examination of the LM literature will also reveal contradictions that have lingered in empirical studies. In addition, the chapter examines meta-analytic studies that used ILM constructs and operational performance as independent and dependent variables, respectively.

In chapter two, the study's methodology, including the research design, primary studies, inclusion and exclusion criteria, coding of the studies, and the interpretation of studies, is included. The statistical model for data analysis, the correction of statistical artifacts, moderator analysis, and the test for publication bias are all presented in detail.

Chapter three presents the results of the study. Different tables, graphs, figures, and illustrations are included to better explain the results besides the theoretical framework. According to the research questions, the results have been presented in that order, and the hypotheses tested.

In the final chapter, conclusions and discussions from the study finding and a summary of the study are presented. Last but not least, the research's contributions, shortcomings, and recommendations for further research are discussed.

# CHAPTER 1: THEORETICAL AND CONCEPTUAL FRAMEWORK

## 1.1 Introduction

The initial review of the lean manufacturing literature was in the 1980s, and it was tied to Taichi Ohno's Toyota Production System (TPS) (see, for example, Ohno, 1988). As a concept, LM was explained in detail in the article by Krafcik (1989), i.e., “Triumph of the lean production system.” For LM, the first authors focused on JIT and Jidoka due to the measurable performance targets they aimed to achieve (Monden 1983, Pettersen, 2009). The Just-in-Time (JIT) system was first credited with removing waste, reducing inventory, and increasing production (Ohno, 1988; Liker, 2004).

The publication of Womack and Jones' book "The Machine That Changed the World" in 1990, which established the LM classification for the collection of concepts and tools involved in the TPS, heralded the LM turnaround (Carvalho et al., 2017). And then, subsequent definitions and research by Womack et al. 1990 and other researchers were done. For their part, (Womack et al., 1990) referred to lean manufacturing as “a production technique which enables firms to utilize fewer resources than before its (LM) introducion while achieving the same amount and value of output or even slightly more for their customers.” This concept highlights the detection and removal of waste in the business' operations using lean tools and practices encompassing everything that does not provide value from the consumers' perspective (see, for example, Nahmias, 2001; Shah and Ward, 2003).

The primary goal of adopting lean manufacturing processes is to minimize waste and increase operational efficiency (Womack and Jones, 2010). Eighty percent of lean is about waste elimination, with the rest being about the system (Shingo, 1989). Overproduction, superfluous motion, excess inventory, unnecessary or costly transportation, rejections/rework, waiting, and overprocessing are the seven types of waste in Japanese often called Muda (e.g., see Cachon and Terwiesch, 2009). Although it may appear that eliminating these wastes is simple and uncomplicated, most firms find it challenging to identify them, and this may require more on-ground data collection, analysis, and review of the worker’s movements, actual time spent on work, the amount of inspections for products, etc., during production processes.

ILM procedures are created to assist employees to solve problems on the shop floor through a people-focused system in which people are engaged in continuous improvement projects (Liker, 2005). Each ILM technique can be used to remedy a specific situation. For instance, TPM ensures machine availability and reliability, SPC ensures making decisions based on process data which empowers planners and workers to keep processes within defined control and avoid any deviations due to common and/or specific causes, continuous flow production helps ensure uninterrupted and smooth flow of production; i.e., in the early stage of continuous flow production implementation, when flaws are discovered, the process is halted, reinforcing the culture of problem identification and ongoing improvement (Sim & Rogers, 2008), employee involvement ensures that operators are part of problem solving, they suggest ideas, form quality circles and are trained and empowered to make decisions (Valente et al., 2020), pull production ensures that production at one station is triggered by the demand from another workstation which limits waste and inventory (Wilson, 2010) and finally setup time reduction saves processing times, reduces changeover times and reduces process changeover waste (Wilson, 2010).

Lean manufacturing has a positive and significant influence on operational performance factors such as productivity, quality, delivery, and customer and employee satisfaction, according to empirical studies (Chavez et al., 2013; Losonci et al., 2013).

However, it is important to appreciate the context in which lean manufacturing is rooted; that is to mention that many firms, for instance, when Toyota, a major discrete automobile business in Japan, started using lean manufacturing in the 1970s, it achieved a lot of success in terms of improved cost, quality, and delivery (e.g., see Dillon & Shingo, 1981). From then on, in the pursuit of operational excellence, numerous firms across sectors, sizes, and geographic locations have attempted to emulate and employ Toyota's lean manufacturing approach.

In the academic circles, much of the lean manufacturing literature focuses more on the application of a mixture of both external and internal lean production (Abru-Ledón et al., 2018). In some instances, external lean production practices, for example, customer focus, supplier development, and lean supply chains in manufacturing firms have been overemphasized (Inman et al. 2010; Panizzolo 1998).

Some studies have shown that applying all lean practices wholly to manufacturing firms might lead to some having a negative impact and others a positive impact (e.g., see Belekoukias et al. 2014; Chavez et al., 2013; Kannan and Tan 2015). Moreover, the challenges of just implementing all of the lean practices multiply when it comes to resource-constrained small and medium-sized manufacturing firms. This is due to the disparities in structure, financial capability, policymaking, procedures, resource utilizations, staff patterns, culture, and patronage between small and large manufacturers (see Welsh and White).

Therefore this study brings to attention the need to scrutinize the direct application of lean manufacturing in discrete-type and process-type industries. It further investigates the likely implication if only internal lean manufacturing is singly taken into consideration from external LM will be able to yield the same or even better results than when combined. The unique characteristics of the different types of firms, that is to say, manufacturing and service industries, offer some challenges on the application of internal and external LP. Because service firms interact more with the customers and suppliers, external lean production practices are more paramount, whereas, in manufacturing firms, internal or shop floor LPs are deemed to be of more positive and substantial effect on the operational performance of manufacturing firms.

## 1.2 Defining lean manufacturing

The substantive definition of the lean concept is considered as varying from one implementer or researcher to another. Much of the research, including by (Bendell 2005; Taj et al. 2011; Shah and Ward (2007), has attempted to define the notion of lean, while other research material casts doubt on whether lean has been effectively and conclusively defined (e.g., see Dahlgaard and Dahlgaard-Park 2006; Lewis 2000; Engström et al., 1996).

Seeking to understand lean manufacturing, although it contains limitless literature as a result of being an extensively researched subject, a good number of researchers on this topic concur that there is still a lack of a consistent or agreeable definition of the concept (Bateman and Hines 2004; Karlsson & Ahlström, 1996; Pettersen, 2009). For the many authors, on the other hand, who have forged different definitions, they have at least come to a more generalisable definition for lean as “less and less of resources or input for more and more of value or output.” It is all about putting in less and less (for the input side) and achieving more of the intended output (e.g., see Ohno 1988; Shah and Ward 2003; Womack et al. 1990).

The concept of lean production is based on the removal of waste and the creation of value (e.g., see Womack and Jones, 1996). In terms of lean manufacturing, waste refers to anything that does not add value to the product or service from the customer's perspective. Hence, waste varies and may include activities that may appear to add value, yet in actual terms, they are not. This waste includes but is not limited to excess production, waiting times, excessive material movement, improper processing, inventory, defects, underutilization of personnel, environmental waste, and underutilization of facilities are all factors that contribute to overproduction (Ohno 1988).

The most comprehensive definition of lean production was presented by Womack et al. (1990, p. 13), and it covered both efficiency and effectiveness aspects of industrial performance. According to Womack et al. (1990), “lean production is lean because it uses less of everything compared to mass production – half the human effort in a factory, half the manufacturing space, half the investment in tools, half the engineering hours to develop a new product in half time. Also, it requires keeping far less than half the needed inventory on site, results in fewer defects, and produces a greater and ever-growing variety of products”.

### 1.3 Internal lean manufacturing practices (ILMPs)

Because of the ambiguity that the LM concept is clouded in, multi-item scales must be used to review lean manufacturing methods (e.g., see Mackelprang 2010). The conceptualization of ILM in this study is based on Shah and Ward (2007)'s work. Hence the interpretation following Shah and Ward (2007) has proven to be successful, widespread and has received unanimous approval and adoption by a large number of scholars working on the subject of LM, either directly or indirectly (e.g., see Azadegan et al. 2013; Filho 2016; Tortorella and Fetterman 2018).

Internal lean manufacturing is just a specific section within the wider lean manufacturing which includes but is not limited to external LM practices, structural LM, human-related LM practices, soft LM practices, hard LM practices, and others. However, the focus here is the internally related lean constructs, also dubbed the internal lean manufacturing practices (ILMPs). The six ILM practices defined by Shah and Ward (2007) are the basis of this research. They include statistical process control, pull production, continuous flow production, employee involvement, cycle time reduction, and total productive maintenance. Much as these ILM practices can be used in isolation from another or individually for performance improvement targets, their true power is derived from being implemented in complementarity and synergistically with one another (Shah and Ward 2003).

Internal lean practices, unlike external practices, find their application on the production floor. They are commonly applied in process and discrete manufacturing industries. This is because, in such industries, there are conversion processes involved, assembly lines, continuous product, and process flow. These practices are applied to the five major components of production (4M+E), namely machines, manpower, materials, methods, and the different media of operation. For instance, setup time reduction and total productive maintenance find applications in machinery, statistical process control, continuous flow, and pull production find application methods. Finally, employee involvement represents manpower.

In the most widely adopted study on lean, Shah and Ward (2007) defined Internal lean as a set of concepts and strategies for improving process efficiency with the goal of enhancing labor productivity and quality, as well as reducing customer lead time, cycle time, and manufacturing costs. Internal lean manufacturing derives its six practices from Shah and Ward's (2003) comprehensive four lean bundles: just-in-time (JIT), total productive maintenance (TPM), total quality management (TQM), and human resource management (HRM). For instance, the JIT practices mentioned include ILMPs like pull production, reducing cycle time and continuous flow production, and are concerned with process flow, minimizing work-in-progress, and eliminating production delays such as technical difficulties, constraints, and other bottlenecks. TQM, as a bundle of LM, encompasses procedures such as controlled process or statistical process control (SPC) which ensure continuous improvement and quality management in the production. TPM covers a set of maintenance practices aimed at optimizing equipment utilization. Employee involvement, a specific section within HRM, which includes techniques such as work rotation, job design, education, problem-solving, and employee participation (Shah and Ward, 2003).

The Shah and Ward (2007) scale was chosen to determine lean practices in businesses since it is the only metric that has been established and substantiated in the literature.

Using previously tested scales to determine the constructs to apply in the literature is recommended in the academic circles (Malhotra & Grover, 1998). As illustrated below, the scale is made up of ten constructs that reflect 48 different lean approaches.

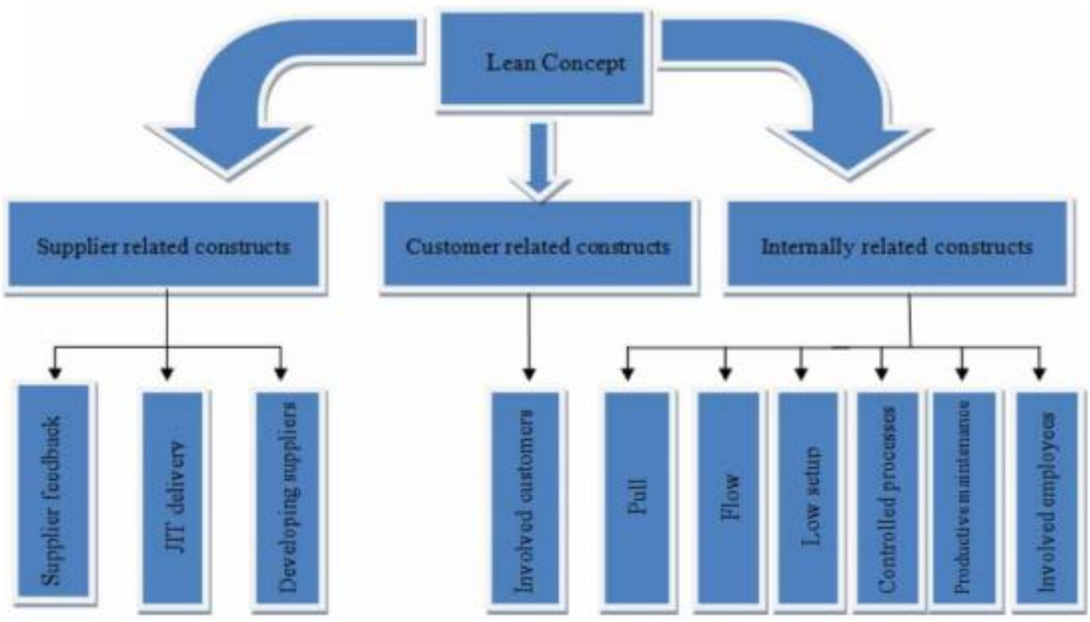


**Figure 1:** Model of lean manufacturing constructs
**Adopted from:** Sezen et al.,(2012). The proposition of a model for measuring adherence to lean practices: applied to Turkish automotive parts.

Internal lean practices including pull production, flow production, low set up times, statistical process control (controlled processes), total productive maintenance, and employee involvement are looked at in this study and are explained in detail.

Each of the internal lean practices has supporting literature(s), as shown in table 1.

**Table 1: Internal lean practices and some of the supporting literature**

| Supporting literature | SPC | TPM | Employee involvement | Flow production | Pull production | Setup time reduction |
|---|---|---|---|---|---|---|
| Panwar et al. (2017) | x | x | x | | x | x |
| Khanchanapong et al. (2014) | x | | x | x | | x |
| Rahman et al. (2010) | | x | | | x | x |
| Belekoukias et al. (2014) | x | x | | | x | |
| Valente t al., (2019) | x | x | x | x | | x |
| Marodin et al. (2017) | x | | x | | x | x |
| Alsmadi et al. (2012) | x | x | x | | | x |
| Sezen et al. (2011) | | x | x | | x | x |
| Chavez et al. (2013) | | | | | | x |
| Juan A. Marin-Garcia and Tomas Bonavia (2014) | | x | x | | x | x |

| | | | | | | |
|---|---|---|---|---|---|---|
| Negrão et al., 2019 | x | x | x | x | x | x |
| Sahoo & Yadav (2017) | x | | x | | | |
| Onofrei et al. (2019) | | | x | | | |
| Al-Zu'bi et al. (2015) | | | | | x | x |
| Nawanir et al. (2010) | x | x | | | x | x |
| Khanchanapong et al., (2014) | x | | x | | x | x |
| Chi Phan et al., (2019) | | | | | | x |
| Wickramasinghe et al. (2016) | | x | | | | |
| Chavez t al., (2014) | | | | | x | x |
| Sahoo (2019) | | x | x | | x | |

One or more of the six internal lean practices in this table are adopted and explained by each of these twenty studies. Below we look at each of the six internal lean manufacturing constructs in detail

### 1.3.1 Controlled process (Statistical process control)

Statistical Process Control (SPC) is a tool for quality control that monitors the process, collects important data or information, and then uses charts, graphs, and statistical methods to put the process under the set limits of quality control (MacGregor and Kourti, 1995). Monitoring the process statistically helps the process managers to identify common and special causes of variation. These are then eliminated and new lower control and upper control limits established. All the process points falling outside these limits indicate process variation. To ensure that the whole process is within limits is the goal of the process monitors. And if this is achieved, the process then operates smoothly and efficiently, yielding more specification-conforming output with less rework or scrap (waste). SPC can be introduced to these processes where the conforming product (product meeting specifications) output can be measured quantitatively. Some of the tools applied under SPC are control charts, flow charts, Gantt charts, Pareto charts, SQC charts, kaizen, and experimental design charts.

SPC as a quality improvement tool that encompassed the control chart with statistical control was first introduced by an American scientist Walter A. Shewhart in the 1920s.

One of the main advantages of statistical process control is that it puts quality control in the operator's hands or the rank and file workers. That is to say that the operators follow the process on their machines and record any anomalies. They leverage the quality data they collect, then do an evaluation of the data using SPC tools, sometimes in consultation with their production supervisors (MacGregor and Kourti, 1995). The result is that the process flow is streamlined with fewer defects or variations as operators are quick to establish if the process is going out of control at any one given point before defective products are made at the end of the line. Doing so ensures that defects or any other form of anomalies are prevented from occurring; rather than letting them occur, they take the effort to detect them and repair them. The basic line is that statistical process control helps the individuals doing the task to know if they're creating conforming products and to take corrective action if processes start to drift out of control (Berk & Berk, 2000).

By collecting and analyzing the information or data from samples at the different temporal and spatial points within the process, wide deviations in the process that may negatively impact the 'fitness for use' of the end product or service can be detected and fixed, thus mitigating waste and the external costs of production like the return of goods, loss of goodwill from the customers, guarantee/warranty costs, etc., which result from the likelihood that defective products not caught by process control and inspection are delivered to the customer.

Process cycle-time reductions and process improvements have turned SPC into a valuable quality evaluation tool from both a cost reduction and waste minimization from the firm's standpoint and high-quality assurance, value, and increased satisfaction from the customer's standpoint. Because SPC underscores early defects or problem detection and prevention, this puts it at a more distinct advantage over other quality control methods, such as sampling or inspection. This is so because these late process control methods instead emphasize more efforts and resources towards detecting and correcting problems in the product when it has already been made.

Statistical process control can also lead to a lessening of the process cycle time (time needed to produce the product or service). This is partly made possible by the elimination of the time that would be spent on reworks on the final products, and it (SPC) would help in the identification of bottlenecks, process constraints, and other root causes of delays within the process. (Berk & Berk, 2000).

A positive correlation has been observed in a number of studies and also on shop floors (Kiran 2017; Negrao et al. 2020). This is corroborated as implementation of SPC using some of its tools like process monitoring, collecting data on variances in processes caused by common and specific causes, monitoring defects, and also deploying the Fishbourne to identify root causes of the effects of anomalies in the operations of the 4M+E (Man, material, machines, methods, and medium) helps plant managers to reduce process variances, stabilize processes and hence achieve leaner processes (Panwar et al. 2019; Marodin et al. 2019). However, in some instances, process management (also SPC) was found not to have contributed directly to OP; the relationship only became significant when mediated through agile manufacturing (e.g., see Khalfallah and Lakhal 2020).

The following operational elements are grouped under SPC according to a model proposed by Shah and Ward (2007) and later adopted by Filho, Ganga, and Gunasekaran (2016).

- Quality at the source: Shop floor staff are empowered to halt production, work on quality issues, or report them to superiors if they arise.
- To identify and eliminate process variations, statistical tools such as matrix diagrams, Pareto charts, histograms, flow diagrams, and experimental design charts are utilized.
- SPC is currently being used on a significant portion of the shop floor's equipment and operations.
- Fishbourne (cause and effect) diagrams are used to determine the source of quality issues.
- On the shop floor, charts depicting defect rates are employed as instruments for improvement.
- Quality teams are pushed to operate in an effective and responsive manner to process deviations.
- To meet established goals and objectives, continuous improvement in existing factory floor procedures is stressed.
- Process improvement plans must lead to changes in improved quality and reduced production costs.
- SPC methods are systematically created and applied to eliminate faults and improve quality.
- Process capability studies are carried out prior to the launch of a product.

- Statistical process control is used to monitor and control all ongoing processes.

### 1.3.2 Pull production system

One of the most essential ideas in internal lean manufacturing is the pull system. It indicates that items are manufactured just when they are needed, not before. Parts will only move in a pull system when they are required at the next stage of the operation (Ohno, 1988). In a wide departure from the pull system, the traditional mass production heavily depends on a push system of production which first forecasts demand and then triggers the need for production and pushing of parts and subassemblies along the production line. A situation like this results in a lot of inventory and overproduction. The primary goal of the pull system, however, is to avoid such inventory levels and overproduction (Liker, 2004). Pull production as a practice of lean production, i.e., It is one of the components of JIT (e.g., see Shah and Ward 2007), seeks to do away with any unplanned production (Smalley 2004, p 17).

Pull as a method of production control is a communication tool between the downstream activities and upstream activities, especially with regard to the needs of each. In a pull production system, a downstream operation on the shop floor or away from the shop floor signals to the upstream operation within the same facility or a separate one with the aid of the kanban card, about what assembly part, raw material, or product is required. That is how much of it, when and the specific station, and where it is needed. Until the downstream customer or maybe the next workstation invokes a need, nothing is produced by the upstream supplier. This runs counter to the principle of push production or mass manufacturing, with advocates pushing until the need arises (e.g., see Smalley, 2017 p. 20)

Customers must communicate their requirements regarding quantity, product mix, quality levels, and delivery dates they want. The end customer or the next operator in the production chain are instances of the downstream customers in a pull system (Dillon and Shingo, 1985). Pull systems are synonymous with a make-to-order approach, and they involve a rapid and seamless flow of production to respond to consumer requests in a timely manner (Liker, 2004). Also space or floor savings that are synonymous with the pull system tend to improve productivity on the shop floor and speedy response to customers’ needs (Mihai et al., 2010)

We cannot study the pull system and conclude it without discussing the *Kanban system*. Kanban has two functions in the lean facility: i) it acts as a communication network system, and ii) it is a tool for continual improvement.

First and foremost, it is a direct order to make material via communication and supply the consumer. The need to produce is triggered by the pull signal. When a consumer withdraws a product, the kanban conveys what the customer has removed, is using, and hence what the customer will require later. This Kanban is delivered immediately to the manufacturing or assembly line. To put it simply, the kanban system is a communication and production loop; it 'tells' the production system to start production out of the realization that some product has been withdrawn from the stores or at a given process stage. This system easily overrides or bypasses some functions of the organization like accounting, forecasting, and planning that not only lags the signal to produce but also generates inconsistency in the production process. The kanban system handles instantaneous occurrences as they are happening on the assembly or production line. The planning systems focus on what the programmer believes should occur. It should be emphasized that no planning method comes close to Kanban when it comes to initiating production with the shortest lead time. The kanban system, in this way, not only reinforces a consistent and reliable supply to the client but also accomplishes it with the least amount of preparation time.

Second, a Kanban system limits total inventory to a set maximum or minimum level. Because each kanban container represents a specific amount of inventory and the number of kanbans is rigorously controlled and limited, this generates a ceiling or the upper limit per se on the inventory. (Wilson, 2010).

Because pull has led to reduced inventories and speedy delivery of products to customers, studies (see, for example, Belekoukias et al., 2014; Rahman, Laosirihongthong, and Sohal 2010) have concluded that the pull system enhances OP. However, Kannan and Tan (2005) found otherwise, i.e., they established a negative correlation between pull and OP instead.

The operation tools under pull production system according to the widely used model proposed by Shah and Ward 2007) and widely used in LM field:

- The pull is a production method in which users order products, and they are created only when ordered.

- The only basis for production is the dispatch of goods from the preceding workstation.
- A production system is created where items are produced only in quantity required, no more and no less.
- Production control is signaled using Kanban, squares, or containers.
- A supplier kanban that rotates between the plant and the supplier is used to authorize the order.
- At each workstation, production is predicated on the present need of the next workstation.
- Suppliers supply in kanban containers, which eliminates the need for further packing.
- For production control, a kanban pull system is employed.
- The shipping of finished items ‘pulls' or starts production.
- The present demand at the next station ‘pulls' (sets in motion) production at stations.

### 1.3.3 Continuous flow production

Continuous production is used to manufacture, produce, or process materials without interruption. It has been linked to enhanced operational performance in a number of studies, including by (e.g., Khanchanapong et al. 2014; Negrão et al. 2020) while others have found some of its major components, i.e., small lot size, to not be positively correlated with any of the operational performance measures (Gonçalves et al. 2019)

Rather than grouping work items into batches, continuous flow is a lean manufacturing strategy that allows for the uninterrupted transit of a single product through every phase of the process. The approach is so named because it makes it easier to bring items to the market on a regular basis. This provides the firm with the opportunity to deliver reliably and quickly goods of more value more often to the customers. This provides the firm with the opportunity to deliver value and often swiftly to its customers, an important hallmark of operational excellence (Alsmadi, Almani, and Jerisat 2012).

It's as easy as beginning work on a product and being focused on it until it's ready to be provided to the consumer.

At first glance, the continuous flow may appear to be less efficient than batch processing because it involves sending smaller amounts of goods to the market at a time. However, it enables more frequent delivery of value to customers, lowering the amount of time they have to wait for their order.

Furthermore, it is an excellent approach to reduce waste during the process. Continuous flow is notably beneficial for lowering inventory costs and reducing the wait time it takes for work items to be completed (Nawanir, Teong, and Othman 2013).

Parts and subassemblies in a process flow do not stop unless to be processed and solely for value-added work, according to the continuous flow principle. It's more of an idea to be realized than a tangible reality. It is the most important instrument for reducing production lead times. The standard approach is to design the process so that each workstation has as little inventory as possible and the workstations are synced as closely as possible. A multi-station cell with zero inventory between workstations is the optimal design. One-piece flow with 100 percent value-adding or value-added work solely is the ideal state we want (Wilson, 2010).

Continuous flow production is mainly applicable in process industries where there is irreversible conversion from one form to another, such as in industries like oil refining, chemicals, fertilizers, synthetic fibers, pulp and paper, iron smelting, natural gas processing, waste treatment, textiles, steel casting, power stations, float glass, etc.

Continuous flow's intention is to extend to 24 hours per day, seven days per week operations with zero or infrequent machine downtimes (or maintenance shutdowns and extended MTBFs). For example, a number chemical plants can run for over one or two years uninterrupted or without a major shutdown. A clearer example of this is the blast furnaces which can be operated between 4-10 years ceaselessly with almost no major shutdown.

To make the most of continuous flow and maintain it as well, it is imperative to make use of the following metrics:

Takt time: The rate at which a product must be completed to meet client demand. Takt time is computed by multiplying the total available production time by the number of required manufacturing units. Takt time allows for the most efficient use of manufacturing capacity to satisfy consumer demand.

More so, lean offers a production leveling remedy called Heijunka to aid in the ongoing optimization of the workflow for Takt time.

Because demand is rarely constant, it is critical to adjust the process to any potential changes. Heijunka is a technique for reducing process unevenness or non-uniformity (Mura) and avoiding overburdening (Muri). It is important for the maintenance of a stable lean system since it signifies "leveling."

Heijunka enables the consistent manufacture of intermediate goods, allowing for fluctuations to be managed according to average client demand.

Another important tool under continuous flow is the Jidoka. The Jidoka is a way of guaranteeing a product's inherent quality. It's also known as "autono-mation," meaning it combines both autonomy and automation. In this way, it allows for prompt halting of the manufacturing process when an error is identified.

There are four distinct steps to it, i.e., i) Discovering an abnormality, ii) Stopping the production process, iii) Fixing the immediate problem, and then iv) Investigating and correcting the root cause.

Implementing Jidoka will aid in ensuring that the product delivered satisfies the end user's quality requirements, even if it momentarily disrupts the process's smooth and continuous flow (Wilson, 2010)

The operational tools of continuous flow, according to Shah and Ward (2007, 2003)

- Products are divided into classes based on their processing needs.
- Products are grouped based on their routing requirements.
- The equipment is set up to provide a steady stream of product families.
- Product families dictate the industrial layout.
- The rate of client demand is exactly proportional to the rate of production.
- The shop floor is set up in such a way that processes and machines are close to one another.
- The factory floor is divided into production cells.
- Processes are clustered together to reduce material handling and part storage time.
- Machines are near together to support just-in-time production.

- Every type of product is manufactured every day to anticipate customer demand variations.
- Various product types are manufactured based on the master schedule from hour to hour and day to day. Small lot sizes are overemphasized to achieve and increase manufacturing flexibility
- Lowering lot sizes or achieving smaller lot sizes in the plant is one of the ultimate goal

Other sources: Hallgren et al. (2009); Nawanir et al. (2010)

Figure 2 is a demonstration of continuous flow production. As seen from the figure, a product is worked on singly, uninterruptedly, and virtually linearly from the input stage to the conversion process and then the output stage. This production type is characterized by small-lot production based on customer demand, low inventory, low manufacturing waste, demand flexibility, and high system productivity (see, for example, Filho, 2020).


**Figure 2: The illustration of continuous flow production.**
**Courtesy figure**: Manoel Gonçales Filho (2020), Functional, structural change of lean and pulled industrial production system: the flexibility case

### 1.3.4 Setup time reduction

The Toyota production system (TPS/LM) was mostly successful because of its ability to reduce setup times, which were previously viewed as a non-value-adding activity that contributed to inefficiencies in the Toyota company's operations (Ohno 1988).

Setup time, also known as cycle time, can be defined according to where it is being applied. For example, in an extrusion production process, setup time is taken as the time it takes to check the machine before it starts, set the machine calibrations to the required measurements, mount the dies, heat the machine, start production, stabilizes production, and then let the production run uninterrupted up to the end.

In printing, setup involves mounting printing plates, mounting rollers of required sizes, and starting and running the machine. In bag making (cutting stage), setup involves mounting blades of correct sizes, starting and adjusting the machine's temperature, and then starting the slitting process with the right calibrations. In other words, set up time in the manufacturing sense can refer to all activities required to be done to set up and prepare the machine to do a particular job.

Setup can also be referred to as changeover or cycle time. It's the time spent in changing the type of the process or the product being processed. The changes may require different settings of the process, and hence it requires time to set this. Therefore, to eliminate waste like waiting time and setup waste, the period of the changeover or cycle time has to be planned, minimized, and well managed.

With the implementation of the lean system, this time needs to be minimized or used optimally.

The duration between the last acceptable unit of the previous run and the first acceptable unit of the next run is known as cycle time (Dillon and Shingo, 1985).

Single minute exchange of die (SMED) and the 5S production theorem are two of the many ways outlined in the lean literature to reduce setup times (Womack et al. 1990).

Sorting, setting-in-order, shining, standardizing, and sustaining are all part of the 5S workstation layout or organization tool. 5S is a simple concept that entails reorganizing the workplace so that components, tools, and equipment are situated close to the operator to reduce time spent looking for them (Imai, 1986). SMED is a collection of techniques that were originally developed to optimize die press and machine tool changeover, but have now been adopted by various manufacturing businesses and processes to minimize setup time to under 10 minutes (Shingo, 1985).

The time it takes to switch from one technique, unit, or product to another is drastically lowered or eliminated with setup reduction. This concept is also known as Single Minute Exchange of Die (SMED) or changeover reduction, with the ultimate goal of lowering changeover time to single digits, i.e., less than 10 minutes. Shigeo Shingo created this in 1989 to reduce the time spent setting up equipment or supplies, as the setup was determined to offer no value; in other words, it was a waste of time in the process (O’rouke and Swan, 2018).

Customers typically expect their providers to produce on schedule and with great reliability. The most cost-effective and efficient solution to solve this challenge is to generate small batch sizes. We may also perform a relationship between changeover time and production with the use of SMED. As the batch size lowers, the cost of each component increases since the changeover time will be of fewer parts, resulting in high manufacturing costs when there are continual setups.

Despite the fact that it has been demonstrated to enhance OP by such large amounts, several studies (e.g., Gonçalves et al. 2019; Negrao et 2017) found that quick changeover and SMED practices—both setup time components—were not positively connected with OP.

1.3.4.1 The four phases of setup time reduction

The reduction of setup should be made in four parts or phases (see figure 3). It's normally ideal to run the process over numerous iterations separated by a set amount of time, such as months. The initial stages of setup reduction (also known as SMED) are straightforward and simple, and they might be overlooked by production runs, although they yield the greatest benefits. People are always surprised at how much time is wasted due to disorganization and general chaos.

Improving both of these aspects (internal and external) and eliminating unneeded tweaks will undoubtedly take more time, money, and creativity.

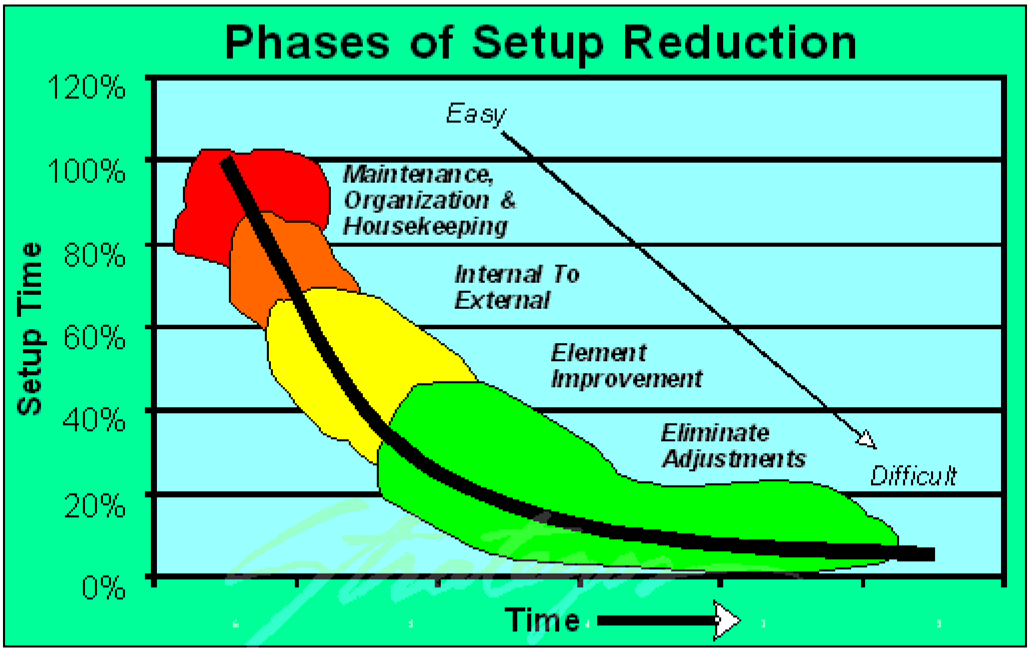


**Figure 3: Kaizen Event or Blitz.**

**Adopted from**: Strategos Lean manufacturing (http://www.strategosinc.com/setup_reduction2.html)

i) Maintenance, organization, and housekeeping

Poor machine and tool maintenance, such as broken spares, filth, ripped and worn parts, worn tooling, and damaged threads are frequently blamed for setup issues. Poor cleanliness, chaotic, untidy, and poorly planned floor layouts are also significant contributors to setup issues. These are simple to organize and should take precedence.

ii) Internal elements to external

When the machine is down, internal elements appear. Examine each internal component to see if it can be done from the outside. For instance, an injection molding die can be first heated while outside before it is put into the machine (Dillon and Shingeo 1990).

iii) Improve elements

Here every component, item, or element is examined to determine how it can be gotten rid of, simplified, or reduce in the period that may be needed to improve upon it.

iv) Eliminate adjustments

Adjustments often consume the largest share of time, they are frustrating to do, and they are susceptible to errors in a setup process. There are a variety of approaches that can be utilized to eliminate them completely, and this should be the ultimate goal of setup reduction initiatives.

### 1.3.5 Total productive maintenance

TPM is a lean maintenance approach that aims to make the most of an organization's resources, such as machines, processes, materials, and labor, to increase production and productivity (Christiansen, 2018).

Over time, the TPM principle expanded from lean methods supporting production to lean principles embracing worker safety and motivation, output quality, and the broader management system of the business (Ahuja and Khamba, 2008; Jaaron and Backhouse, 2011). TPM is a common component in lean manufacturing because it is used to reduce and eliminate equipment failures while also increasing the mean time between failures (MTBF) (Ahuja and Khamba, 2008). TPM has established itself as an innovative method to machine maintenance that complements other well-known manufacturing strategies such as total quality management (TQM), just-in-time, complete employee involvement, and continuous performance improvement (Cua et al., 2001; Ollila and Malmipuro, 1999; Yamashina, 2000).

Upon re-examination, lean manufacturing has over-emphasized the need of enhanced maintenance management in improving an organization's competitiveness and effectiveness (Ahuja and Khamba, 2008; Riis et al., 1997). Manufacturing companies have explored a variety of techniques to increase maintenance effectiveness over the last two decades (Roup, 1999). The development and execution of a total productive maintenance (TPM) plan has been highlighted as one of the techniques to increase the performance of maintenance activities (Ahuja and Khamba, 2008)

Through the engagement and encouragement of the entire workforce, TPM as a manufacturing program aims to maximize equipment effectiveness and prevent breakdowns (Nakajima, 1998). It aids in maintaining plant and equipment at peak productivity, dependability, operability, and availability (Ahuja and Khamba, 2008; Shah and Ward, 2007). Zero defects, zero breakdowns, zero accidents, and a shorter mean time to repair (MTTR) is the ultimate aims of TPM (Ahuja and Khamba, 2008). TPM is a safety, quality, production, and personnel motivation/satisfaction policy, as well as a maintenance-specific policy (Ahuja and Khamba, 2008).

TPM entails a variety of procedures. Predictive or preventive maintenance, maintenance optimization, safety improvement programs, planning, scheduling techniques, and new process equipment or technologies are the five elements of TPM identified by Shah and Ward (2003). Similarly, Cua et al. (2001) identified three primary practices: autonomous and planned maintenance, a focus on technology, and proprietary equipment creation and improvement. As a result, TPM can be a useful tool for increasing a company's technological base by enhancing equipment technology and improving personnel skills and knowledge (Cua et al., 2001; McKone et al., 2001).

TPM is an innovative approach to machine maintenance that involves every employee, from top management to factory floor workers, to enhance equipment effectiveness or efficiency. It allows planned maintenance by motivating workers and allowing small groups to operate independently (Nakajima, 1988). Accordingly, Willmott (1994) further expounds on the earlier definitions of TPM by early researchers as: “Maintaining and improving the integrity of the production systems through the machines, equipment, processes, and employees that add value.”

The backbone of TPM is made up of three major concepts: increasing equipment efficacy, autonomous maintenance, and teamwork. TPM is one of six internal lean techniques that improve preventive, corrective, and predictive maintenance while increasing equipment efficiency and profitability (Ahuja and Khamba, 2008).

TPM enhances total equipment productivity, reduces machine downtimes by decreasing breakdowns, optimizes operators' health and safety, and encourages autonomous maintenance by delegating important operations to operators in the organization's daily routine activities (Bhadury, 2000). Researchers such as (Ahuja and Khamba, 2008; Belekoukias et al. 2014; Rahman et al. 2010; Valente et al. 2020) have proven that TPM has a positive and significant influence a firm's manufacturing performance.

TPM also requires that staff take proper care of their equipment and processes, as well as being fully supported and empowered in making autonomous, predictive, and corrective maintenance decisions (Willmott, 1994). Some of the simple preventive maintenance activities operators can do on their machines is lubrication, ensuring machine cleanliness, reporting any unusual behavior with the machine, keeping downtime records of the machines, and following operational procedures when operating the machines. Therefore, the importance of worker participation as one of the major factors in the TPM's success cannot be overstated.

However, for all its great contribution to OP, TPM, as Belekoukias, Garza-Reyes, and Kumar (2014) established, had a very limited impact on OP and sometimes even triggered a negative effect in some OP dimensions.

The measures of TPM according to G.L.D. Wickramasinghe and Asanka Perera (2016), Ahuja and Khamba 2007, 2008)

i) Autonomous maintenance: This includes tasks such as developing and improving operator skills, encouraging operator ownership, and cleaning, lubricating, adjusting, and repairing production equipment. Giving operators specialized training to increase their machine care and maintenance skills, as well as the autonomy or authority to clean, maintain, and make minor adjustments to their machines, are examples of evaluation.

ii) Individual improvement. Systematic loss identification and estimation, loss structure and mitigation, enhanced system efficiency, and overall equipment efficiency and effectiveness are all part of this process. An example of an evaluation of an item under individual improvement could indicate that processes are in place to identify and eliminate losses in a systematic way.

iii) Planned maintenance: It entails tasks such as developing an effective and efficient preventive maintenance system, creating preventive maintenance checklists, and reducing the mean time between failures and recovery time. The outcomes of ensuring that the organization has effective and efficient maintenance procedures to reduce machine stoppages, increased downtimes, and MTTR due to failures, for example, were used to measure planned maintenance.

iv) Quality maintenance. It includes tasks such as reducing defects, following up and providing redress to the machine problems and their root causes and establishing the (5M+E), i.e., machines, manpower, materials, methods, and media. The yardstick of evaluating TPM as a technique for reaching zero defects may be used to monitor quality maintenance.

v) Training and development: for example, imparting technical skills, quality control skills, interpersonal skills, cross-functional workforce, aligning employees' expectations with the organization's objective, and skill upgrading and evaluation on a regular basis. Evaluating and assessing the number of organized training programs an organization has in place to achieve multi-skilling and cross-functional training of personnel can be used to gauge education and development.

vi) Safety, health, and the environment: This category includes actions like ensuring a safe working environment, providing a suitable work environment, and preventing injuries and accidents. The company's safety measures and equipment installed on the machinery to ensure employee safety were used to assess safety, health, and the environment.

vii) TPM for the office. Include operations like improving synergy across multiple company functions, removing procedural bottlenecks, focusing on cost-related concerns, and implementing 5S in the office and the wider workplace. The degree to which a corporation places a significant focus on close interdepartmental contacts and getting work or tasks done and effectively completed on time, for example, can be used to measure or grade office TPM.

viii. Planning and development. This includes ensuring that there are few difficulties and that new equipment is operational on time, as well as transferring knowledge from old systems to new systems and maintaining improvement programs.

Credit: G.L.D. Wickramasinghe & Perera (2016)

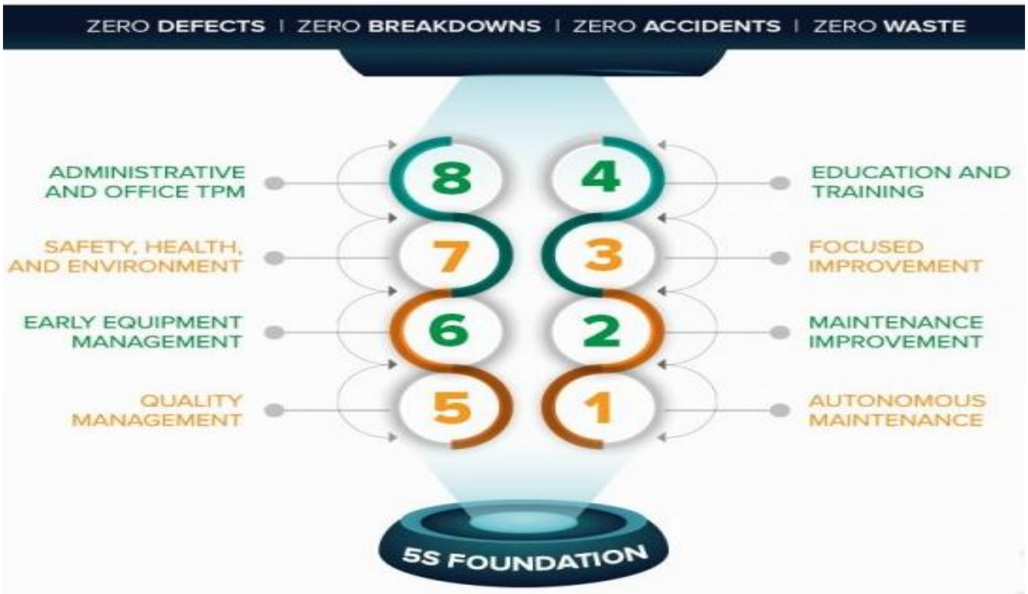


**Figure 4: The structure of TPM**

**Source:** Bryan Christiansen (2018), The Challenges of Implementing Total Productive Maintenance

In figure 10, TPM as a complex process is seen to be divided into two components, i.e., 5S and the eight (8) pillars, which have been described above in accordance with G.L.D. Wickramasinghe & Perera (2016).

### 1.3.6 Employee involvement

Employee involvement is a smaller part within HRM centered on decentralization of power and the blurring (or reducing) of organizational authority layers, promoting teamwork, management-worker communication, in-plant collaboration, and multi-functional and cross-functional training policies (Kenney and Florida 1993; Monden 1983).

According to the resource-based view (RBV) theory, a firm's competitive advantage is derived from its unique, inimitable, and difficult-to-replace valued resources (Barney, 1995). In this way, the firm’s workforce can be referred to as a strategic resource in the successful LM implementation when it achieves competitive growth and adds value to the organization (Huselid, 1995).

Depending on the firm background, EI is referred to as engagement, participation, and empowerment of the rank and file workers, the middle level up to the top-level workers in the decision making of the organization. Organizations with a deliberate policy to improve in-house are often astonished at the significance of employee involvement in every type and level of work which they were not taking seriously before a lean approach is introduced.

The employee contribution to the design and implementation of LM programs (e.g., see Knudsen 1995), as well as their input into daily decisions such as setting objectives, assigning tasks, and job rotation (Delbridge, Lowe, and Oliver 2000), has been hailed as critical to successful LM (JIT) initiation and implementation (Bello-Pintado, and Merino-Daz 2008).

Employee involvement can as well be construed as the direct participation of the organization’s workforce in a bid to help the firm stick to its mission statement and achieve its objectives by utilizing their concerted efforts, experience, concepts, ideas, and expertise towards making informed decisions to tackle wide-ranging problems in every function of the organization (Valente et al., 2020). According to this definition, participation can be regarded as representative participation, staff motivation initiatives, direct communication, and upward issue solving.

A culture of work excellence, multi-skilling training and monitoring, an employee suggestion system, information exchange, and team-based improvement are all examples of employee involvement (Rahman and Bullock, 2005)

In the analysis of LM models, studies have recommended including employee involvement and participation practices (Cua, McKone, and Schroeder 2001).

The literature highlights the most prevalent human resources methods that favor employee involvement, such as providing workers with information, remuneration, skills, motivation, and power (MacDuffie 1995). These strategies can transform the workforce into a source of long-term competitive advantage over the company's competitors (e.g., see Guerrero and Barraud-Didier 2004). They have also been shown to be timeless critical keys in the deployment of lean manufacturing in manufacturing enterprises (Nordin et al., 2011).

Within human resource management, education and development play a great part as well as to lean manufacturing as a whole. It comprises sub-areas like technical training, quality management, interpersonal skills, multi-skilling, aligning the workforce with the organization's objectives, and regular skill review and upgrading. Staff education and development are measured, for example, by including and ensuring that the organization has a structured training program in place to accomplish employee multi-skilling (Wickramasinghe and Asanka Perera 2016).

Employee participation is the core principle driving practically all research examining high-performance work systems and organizational performance, according to a review of the different literature (Cappelli and Neumark 2001). According to Forza (1996), "many scholars and practitioners unanimously concur that employee involvement is a vital feature of LM implementation." However, some studies have found that while employee involvement does not have a direct impact on operational performance, it does enhance or facilitate the adoption of LM, which has a direct impact on operational performance (Fullerton and McWatters 2002). In other words, this is an instance where employee involvement can be construed to be a positive mediator or moderator of the lean manufacturing– operational performance relationship. It indirectly has an influence on the LM-OP association.

The crucial practice of targeted improvement is a part of employee involvement. It focuses on the primary wastes, variability, and other issue areas that lean covers to ensure improvements in the organization's core performance areas. It is involved with building problem-solving structures and abilities at all levels, identifying areas for improvement, formulating goals, and putting the recommended improvement activities into action. (Kovács and Andrea Ko, 2020). Problem-solving and employee development is an essential feature of an effective employee involvement policy for lean firms (Benson, Finegold, and Mohrman 2004).

To this, teamwork can be included. This comprises building shop-floor goal planning, goal alignment, performance management, and communication routines for self-sufficiency, ownership, and accountability to empower individuals at work to reach a common goal of enhanced performance.

The ability to measure and control performance is also a key component of EI. It assists in ensuring that work processes are well-designed and controlled and that performance targets are fulfilled through standardized work methods and short-interval performance-control systems. Deviations or changes from standards and targets will be readily evident, allowing for real-time remedial action (Andrea Ko and Kovács, 2020)

The most cited employee involvement principles namely employee empowerment, training, communication, and rewards, have been those proposed by Lawler (1986). Employee involvement leverages more employee commitment (Flynn et al., 1995), and it distinguishes between lean and non-lean adopting firms by facilitating information sharing and empowering employees to identify and solve problems as they arise. (Sakibarara et al.,1997).

As a result of the increased employee participation, i) the organization's decision-making competence improves (e.g., see Apostolou, 2000) ii) workers' attitudes toward work are enhanced (e.g., see Leana, Ahlbrandt, & Murrell, 1992) iv) significantly raised employee satisfaction or fulfillment (e.g., see Freeman & Kleiner, 2005) iv) lower costs due to waste minimization and shorter product cycle and changeover times (e.g., see Apostolou, 2000) v) increased employee productivity, efficiency, and engagement across the industry (e.g., see Apostolou, 2000) and vi) Empowerment, better performers, creativity, commitment, and motivation, as well as reduced work turnover (see Apostolou, 2000; Jones, Kalmi, & Kauhanen, 2010).

According to (Shah and Ward 2007; Vathsala Wickramasinghe & G. L. D. Wickramasinghe 2017), they centered employee involvement more on information and knowledge sharing between employees and fellow employees and employees and their managers. It's by no mistake that the great number of operational tools they advocated for under employee involvement as a practice of internal lean manufacturing involve Eighty percent of the activities to do with creating systems that collect, store and share information throughout the organisation. Communication has been touted as a major feature for the successful implementation of EI by other researchers too. After having an information bank, lean enterprises have created avenues of ensuring easy access and proper dissemination of information to all the employees in the organisation (Vathsala Wickramasinghe & G. L. D. Wickramasinghe 2017).

Not to take away its enormous positive contribution to the OP, a minimal number of studies found employee involvement, especially the flexible, cross-functional teams and some HRM aspects to be not positively correlated with OP (Gonçalves et al. 2019)

Some of the operational tools and action plans under employee involvement suggested by Shah and Ward (2003); V. Wickramasinghe & G. L. D. Wickramasinghe (2017) and Bento & Gérson-Tontini 2018 an organisation include:

Quality circles: These are groups of employees created by team leaders. They give opportunities to work on projects as teams in which tasks and responsibilities are shared or delegated among the team members.

Suggestion teams: Teams of all kinds of workers with different ideas formed as suggestion schemes. Channels or lines of communication are created within the organizations and made available to employees to bring forward new ideas for improvement in the production within the organization.

Consultation meetings: These are periodical gatherings of employees to discuss problems they face on the shop floor, and they are encouraged to share ideas.

Delegation of responsibility: This occurs most often from the top to the bottom of a company, where individuals are given clear authority and obligation to deal with their production concerns and customers on a daily basis.

Quality at the source: A set of steps taken by the company to attain perfect quality the first time. If a mistake happens during the process, it must be discovered, assessed, and corrected immediately. Then a record must be made, and precautions must be taken to ensure that it does not reappear in the future.

Problem-solving refers to the actions done by a corporation to identify and examine the root causes of problems, as well as methods to remedy them and ensure that they do not reoccur. Problems must be tackled with an open mind and then analyzed using facts and data to find a long-term solution.

Respect: There are various ways to show respect for others. The greatest thing to do is to foster an environment in which leaders are nourished and developed within the organization rather than being sought out. Leaders are role models for the company's idea and way of doing business, and they must be familiar with the daily work routine and the first and best teachers of the company's ideology. Values and conventions in the workplace must be spread and lived for a longer period of time.

Multifunctional teams: These are used to increase labor efficiency, strengthen cross-functional relationships in the workplace, improve quality, and reduce costs to the business by utilizing the appropriate tools.

Teamwork should be promoted. People-related action plans must include idea exchange, training, communication, and programs to reward and recognize the highest-performing teams.

Continuous improvement requires everyone in the firm to work together and actively participate in presenting suggestions for changes. Continuous improvement, also known as kaizen in Japanese, entails incorporating all functions of the firm in operations aimed at continuous improvement. The enhancements are slow and incremental, but they are expected to yield significant benefits over time.

In conclusion, for the most part, studies have shown a positive association between employment programs and LM (Bonavia and Marin-Garcia 2011; Hiltrop 1992).

### 1.4 Operational performance metrics and measurement

According to this study, the major objective for advocating the application of lean in the function areas of the organization is to achieve the nine operational performance metrics listed in the study. Each of the operational performance dimensions explained in detail represents each of the goals that implementation of ILM seeks to achieve.

Performance measurement is a procedure of enumerating action steps of a specified task and can be used to measure the efficacy, suitability, and effectiveness of an action taken towards accomplishing pre-set organizational objectives (Neely, Gregory & Platts, 2005). However, a number of scholars and practitioners have recognized various scenarios and production areas where performance measurement may be useful. Little guidance on how to identify and apply the relevant performance dimensions to monitor and gauge company performance has been provided. The use of operations performance measurements is proving effective at the production level in the domain of lean manufacturing, because it is increasingly frequently used on the shop floor, especially in connection with the production process (Abdel-Maksoud, Dugdale, & Luther, 2005). Operations performance in the context of production has been shown to be influenced by the prevailing operating conditions and to reflect some internal characteristics of the processes and the production system (Bartezzaghi & Turco, 1989).

LM is mostly used on the shop floor for production and is linked to production operations. As a result, using non-financial criteria or measurements to establish the results of LM implementation, which are not included in traditional accounting systems, appears to be a more realistic and relevant yardstick in enumerating lean initiatives (Abdel-Maksoud et al., 2005). This means that LM adopting enterprises are more likely to utilize non-financial measures to determine the advantages associated with ILMPs than financial measures. Non-financial measurements are used to assess how well and on time a company's activities are carried out, which impacts the company's overall operational performance. According to Bartezzaghi and Turco (1989), Chang & Lee (1995), and Jeyaraman Leam (2010), OP is influenced by shop floor operating conditions and indicates production outcomes at each level.

Operational performance has typically been measured in terms of the organization's operations strategy's competitive priorities (for example see, Narasimhan and Das, 2001). Hayes and Wheelwright (1984) coined the competitive phrase priority to describe a company's strategic preferences or dimensions from which it chooses to compete. However, according to this study, to gain a competitive edge, manufacturing capabilities must be strategically aligned with competitive priorities, such as operational performance (e.g., see Hayes and Wheelwright, 1984).

The operational performance or manufacturing plant performance is determined in terms of various dimensions, including the manufacturing plant's labor efficiency (Arthur, 1994), first-pass yield (Panwar et al. 2018), lead time reduction (Negrao et al. 2020), machine efficiency (Youndt, Snell, & Lepak, 1996), conformance quality (Cua, McKone, & Schroeder, 2001; Swink, Narasimhan, & Wang, 2007), manufacturing plant productivity (Ichniowski, Shaw, & Prennushi, 1997), schedule attainment (Bozarth, Warsing, & Flynn, 2009), on-time delivery (Cua et al., 2001; Swink et al., 2007; Youndt et al., 1996), Inventory control (Hofer, Eroglu, & Hofer, 2012; Youndt et al., 1996), production volume flexibility (Cua et al., 2001; Swink et al., 2007), and manufacturing cost efficiency (Bozarth et al., 2009; Swink et al., 2007).

Several earlier research, according to Swink et al. (2005), has preferred to consider operational performance as an aggregate construct rather than breaking it down into its separate components or dimensions. Similarly, Flynn et al. (1995) and Ketokivi and Schroeder (2004) argued that operational performance is typically measured as a composite of various performance factors and that it must be studied as such because it is in most times seems multidimensional.

The relationship between internal lean practices and several operational performance dimensions has been studied in a number of empirical research (see Callen et al., 2000; Fullerton and McWatters, 2001). Individual measures for internal lean practices and/or operational performance, on the other hand, can occasionally fail to represent the considered constructs of each of the dependent and independent variables adequately (i.e., ILM and OP). While internal lean practices such as just-in-time, quality, and SCM efforts are synergistically supportive, some exceptions such as Kannan and Tan (2015) discovered that the organization's efforts in the practice of total quality management have the most visible and direct impact on business performance.

According to Belekoukias et al. (2014), JIT and automation have the greatest impact on operational performance, while kaizen, total productive maintenance (TPM), and Value Stream Mapping (VSM) appear to have a minor or even negative impact (OP). This drives the point home that internal lean manufacturing processes may be more closely linked to specific operational performance metrics than others.

In contrast to the previous findings, this study examines the potential for different relationships between aggregate internal lean practices and individual ILM practices on aggregated operational performance, which includes dimensions such as on-time raw material delivery, production flexibility, manufacturing cost, productivity, lead time reduction, and defect reduction (e.g., see Belekoukias et al. 2014; Khanchanapong et al. 2014 and Rahman et al. 2010).

Below we look at each of the considered operational metrics for this particular research and how significant it is for firms to have these dimensions as effective and enhanced as possible and the overall effect on the composite OP.

### 1.4.1 Manufacturing cost

Manufacturing cost is the sum of the costs of all input, for example, energy, labor, capital, IT, raw materials, equipment, etc., that are needed in the process of designing, developing, and making a product (Kenton and Kindness, 2021)

As a dimension of operational performance, cost reduction remains one of the major but elusive targets of many manufacturing firms. It is also directly proportional to the waste and inefficiency in the process. Ohno (1988); Shah and Ward (2007), and Womack et al. (1990) suggested that the quickest way to bring down costs in production is by tackling waste in the process

The manufacturing costs are categorized in a number of classes, but the major ones include direct costs, indirect costs, external costs, and internal cost of production. The entire delivery cost is heavily influenced by production costs such as direct materials, direct labor, and manufacturing overhead.

Manufacturing costs, for the most part, are directly proportional to any changes that occur in production volume. That is to say that the expenses incurred as a result of manufacturing escalate as production increases (e.g., see Beers and Drury 2021).

In manufacturing, companies also make use of the learning curve, where they are presented with the opportunity to achieve lower costs as production expands. This is because, in due process, operators learn to run the machines, and therefore they make fewer errors as they become more experienced. Hence, they can produce more items in a given time period than before. Therefore, the economics of manufacturing costs like the learning curve and the rest can motivate the businesses that want to achieve a lower average per-item fixed cost (e.g., see Altunışık and Torlak, 2015). However, in other instances, the average cost per item may not change substantially because additional production, in some cases, always generates additional manufacturing costs (see Altunışık and Torlak 2013).

Direct expenses of manufacturing costs fall into three broad categories, namely materials, labor, and overhead. That is, the salary and supplies of the foreman are included, but the salary of the organization’s secretary or the secretary's office supplies are not included.

Fixed costs of production typically include equipment, rent, production space, assets, furniture, machinery, etc. For such costs, nothing changes as a result of using more or less of the mentioned items or the volume of production. Conversely, variable costs have an inversely proportional effect on production volume changes in the firm. Examples of variable costs include worker’s wages/salaries, energy, raw materials, capital, supplies, and many others (e.g., see Beers and Drury 2021).

When determining the wholesale price of an item, manufacturing companies estimate their overall spending in terms of the cost of production per item. It can be deduced from most studies that the firm’s earnings increase when the production increases, but for most of the fixed costs, they remain steady.  Therefore, as the firm’s operations become profitable, the average expenses accrued per item fall as well (Hofer et al., 2012).

In its broadest meaning, cost-effectiveness comprises lowering the cost of operations in terms of repairing defective items to meet quality criteria (reworks) and other internal failure costs (i.e., defect, scrap, rework, process failure, price reduction, and downtime). And this should consequently translate into having lower manufacturing costs compared to those of the firm’s competitors (see, for example, Russell and Taylor III 2008)

### 1.4.2 Productivity

It's the ratio of input to output. Simply put, the output is materials that are produced, while input is what is required to produce the output. Most times, this ratio is a representation of an average output expressed as goods produced divided by the average input of i.e., machinery, energy labor or raw materials, etc. (Kendrick, John, and Frankel, 2021)

In other terms, productivity can also be a measure of a person taking on an allocated task and effectively and efficiently completing it.  There is always a misconception that productivity is getting things done right. Wrong. Productivity should be geared towards doing only the right things efficiently and consistently (see Clear, 2019). Furthermore, being productive is about emphasizing a steady speed on specific operations and not maximum speed on all the activities (Clear, 2019).

Labor can also be a form of productivity. Lean adoption also aids in the attainment of labor cost reductions.

Last but not least, process-type industries' processes are typically carried out at high pressures and temperatures, resulting in significant energy consumption. TPM, pull production, and quality management is examples of lean approaches that assist process industries make the most of their equipment and machinery. As a result, energy consumption is reduced, and productivity is increased (see, for example, Panwar et al., 2017).

### 1.4.3 Quality

This is the adherence to internal specifications, that is to say, percentage within internal specification limits. Quality also refers to a product's or service's suitability for usage as well as its ability to meet the needs and expectations of customers (Barry, 2011). Quality is discussed in terms of product performance, product endurance, product convenience, and product acceptance within the design parameters when measuring operational performance (Sohal et al., 2010). The longer a product lasts or, the longer it takes for it to break down, the higher its durability (Williams, 2013). As a result, firms always assess product durability by looking at the average duration between manufacture and final consumer use.

Acceptable quality levels could indicate that our product is of higher quality than our competitors' (Bhasin 2008; Flynn et al., 1995); and that actions for repairing defective items to meet quality criteria (reworks) have decreased (Fullerton et al., 2009).

First, internal lean techniques have been related to high levels of quality because they strive for perfection by continuously removing layers of waste (Nakamura et al., 1998; Li et al., 2005). Kannan and Tan (2005), for example, produced evidence that product quality was the most consistently generated performance objective engendered by the internal lean manufacturing practices.

ILMPs such as statistical process control and kanban containers have been linked to a drop in scrap and rework, and thus a reduction in the frequency of inspections (Fullerton and McWatters, 2001). Other internal lean manufacturing strategies, such as staff participation and management commitment, have also been demonstrated to increase product quality and defect prevention (Lawrence and Hottenstein, 1995).

The thoughts of quality as an innate or inherent attribute of goods and not just merely adding some stuff to them make it easier for quality to be objectively evaluated (Garvin, 1984) depending on who defines or perceives it as elaborated below:

• User-based approach: views the quality of a product as nothing more than what the individual consumer perceives, defines, or says it is.

• The manufacturing-based approach: An approach primarily concerned with the supply side of the quality perception equation. This strategy emphasizes engineering and manufacturing procedures that, if followed, will ensure that the final product or service meets pre-determined requirements or specifications.

• Value-based approach: This method defines quality in terms of the product's cost and pricing. A product that costs relatively less to produce and is offered at a fairly acceptable price is considered to be of higher quality than a product that is costly to produce and so expensively sold to the final user. (Courtesy: Mohammed, Y.J. 2019)

According to Panwar et al. 2018, they list some of the operational tools under quality as

i) Products that do not fulfill quality standards are minimized.

ii) Having greater product quality in comparison to the competition

iii) The amount of low-quality items that must be thrown (scraps) is greatly decreased.

iv) The percentage of products passing final inspection on the first try (first-pass quality yield) has risen.

### 1.4.4 On-time delivery

Nawanir et al. (2012) sums up speedy delivery as:

i) an increase in the speed with which products can be delivered to the market.

ii) an enhancement in the company's ability to deliver products to customers on time.

iii) Improving the company's capacity to put products to market faster than its competitors.

To avoid shortages and satisfy production schedules, auxiliary materials (inputs other than key raw materials) and packaging materials must be delivered on time (e.g., see Panwar et al. 2017). Internal lean approaches such as pull production, Kanban, and continuous flow production have reduced production interruptions caused by shortages of auxiliary materials, packaging materials, and raw materials, resulting in bettering the meeting of delivery dates.

Internal lean manufacturing strategies, such as adherence to daily production schedules, have been shown to improve on-time delivery (Cua et al., 2001). According to studies like Fullerton and McWatters (2001), the benefits most frequently highlighted by JIT adopters were improvements in queue time, movement time, machine downtime reduction, and total throughput time. These benefits than had an indirect impact on the speedy delivery of products manufactured on the shop floor to the intended final consumers.

On-time delivery is one of the most important Key Performance Indicators (KPI) in the manufacturing industry. If orders are not finished and delivered on time, buyers will leave the business, and attracting and earning new clients would be tough. The application of ILMP will increase on-time delivery by a greater proportion by improving equipment availability and effectiveness, defect prevention, scrap reduction, and rework reduction. A large amount of research shows that ILMP has a positive and considerable impact on on-time delivery (Cua et al., 2006; McKone et al., 2001).

### 1.4.5 Flexibility

Production flexibility refers to a production system's ability (readiness) to adjust quickly and successfully to any real or perceived changes in the external and internal environment, as well as the changing product and process requirements (Swamidass P.M. 2000). Similarly, it is the ability of the production system to adapt well to environmental or factory-floor instability. The manufacturing plant's flexibility allows it to maintain production and operational flow in the face of change and uncertainty (Swamidass P.M 2000).

Flexibility gives a company 'room of maneuver' to respond to changes in market conditions by making adjustments to its internal operating media in a timely and cost-effective manner (Watts et al., 1993). As a result, flexibility in this area can be thought of as a response to supply chain disruptions for raw materials, completed goods, and other operational risks. Flexibility can take many forms, including output mix flexibility, changeover flexibility, volume flexibility, rerouting flexibility, and material flexibility, to name a few (e.g., see Gerwin, 1993). It enables businesses to modify volume and mix of output to satisfy market and/or manufacturing demand in the face of uncertainty in customer demand, raw material demand, and preferences (D'souza & Williams, 2000; Gerwin, 1993).

According to (Paul M. Swamidass 2020), the manufacturing flexibility at the facility or plant level, a complex blend of several ingredients is usually a big part of this, and it includes:

(i) hard technologies (hardware, software, and equipment),

(ii) soft technologies (i.e., know-how, procedures, organizations, and techniques)

(iii) design and

(iv) manufacturing infrastructure.

Internal lean approaches such as flow production and pull manufacturing can enable product variety, volume flexibility, and reduced lead times without incurring excessive expenses (Gerwin, 1993). Upton (1995), for example, discovered that JIT production processes have a favorable and considerable impact on changeover flexibility, or the ability to quickly replace existing items with new ones. Other internal lean manufacturing strategies, including small-lot size production, pull strategy, cellular manufacturing, and kaizen (continuous improvement), are also favorably associated with the new product type and process flexibility, as well as production volume flexibility (Swink et al., 2005). Fullerton and McWatters (2001) discovered empirical support for quality management, JIT purchasing, and kanban systems positively improving flexibility.

### 1.4.6 Waste minimization:

It's a collection of activities and practices aimed at reducing the generation of non-value-adding items and activities (see Panwar et al., 2017).

In comparison to non-lean adopter enterprises, lean adopter firms enjoy a large reduction in waste (Shah and Ward 2003). Lean adopter companies have implemented a variety of lean methods, including visual control, VSM, 5S, and continuous flow, which enable seamless process flow and have helped to reduce losses caused by delays, unexpected buffers, stockpiling, and other production bottlenecks. Furthermore, many process-oriented firms have suffered significant losses as a result of inventory leaks and damage in storage. With the adoption of TPM, 5S, and visual control, such as andon and Jidoka, as well as JIT pull techniques, lean adopter organizations have discovered various ways of mitigating these losses (see Panwar et al. 2017).

Lean manufacturing practices can help decrease facility waste by i) Reducing waste caused by excess inventory and overproduction, ii) Minimizing labor expenditures related to unnecessary motion, iii) Decreasing transportation-related waste, and iv) Reducing over-processing waste (Ohno 1988).

According to Mimeo (2019), some of the waste minimization operation tools include:

- Understanding the value of your end product
- Identifying waste and then classifying the types of waste
- Identifying potential workplace waste

- Perfect tune-ups: tiny, consistent, and gradual adjustments and inspections can help you get to a lean end product quickly.
- Creating a manufacturing workflow: Visualizing the step-by-step process of lean manufacturing can aid in the creation of an accessible manufacturing workflow.
- Employee training: Some employees are to blame for the loss of time, money, and even equipment depreciation.
- Creating JIT inventories: This is a method of just stocking materials and tools as they are needed, rather than ahead of time.
- Lean management ensures long-term workplace efficiency.

### 1.4.7 Defects reduction

Because lean manufacturing's major goal is to eliminate waste, achieving the operational performance dimension of zero defects moves us closer to the achievement of total leanness on not only the shop floor but also in other departments of the organization. Internal LMPs like statistical process control involve activities like collecting data on the defects using Pareto charts to understand the trend of defective products and production process inspections which all contribute to the elimination of defects (Sezen et al. 2012)

Every manufacturing company has its own set of specific methods for developing its own products. These products are made with outsourced components, raw materials, and machinery. Different products may have different levels of quality (Mohamed and Shabana 2016). There may be a few defective products among a batch of perfectly operating products due to unavoidable circumstances. When the rate of defective products supplied to customers is too high and shows no indications of slowing down, it can have major negative consequences for the firm's brand image and reputation. This will certainly negatively affect future sales through the loss of existing customers and scaring away the would-be new customers. Therefore, it is for the good of the manufacturers to discover the percentage of defective products produced by the system so that remedial action can be taken. In this way, blowbacks that may arise from loss of goodwill from their customers or returning of their products leading to costly guarantees can be avoided.

Defects can be reduced in a variety of ways. These tactics can be divided into two categories: the early stage and the late stage. In the early stage of defect detection and prevention, before the manufacturing process can begin, early-stage tactics focus on finding, removing, or preventing faults. In the late-term strategies of defect prevention, action steps are used to eliminate manufacturing faults while the production process is still in progress.

### 1.4.8 First pass yield

First pass yield is a good measure of the leanness of a process and the elimination of waste from the process. The first pass output (FPY) is the number of units coming from a process, which is divided into the number of units flowing into the process over a certain amount of time (Littleman, 2013)

Indicators of the production and quality performance of a line include FPY, also known as FPY. FPY is computed by dividing the number of 'good' units that leave a process without rework or scrap faults by the number of units that enter the same process over a defined timeframe (Boyer, 2019).

First pass yield formula (courtesy: Bartoszewicz, 2018)

FPY = (units of products passed from process to specification with no defects/rework) / (total units of products entering the process)

Many other lean approaches do not cover the costs of repair, but rework can be a substantial share of the time and cost to the final production in many installations (e.g., see Littleman, 2013)

The success of continuous improvement initiatives can also be a good indication of the first step yield. Very often, continuous improvement projects focus on waste reduction and inefficiency that might be hidden from analysis if the results are not assessed in the first place. For these reasons and many others, pass yields are typically considered to be the primary and important phrase of the OEE formulation (Littlefield, 2013).

### 1.4.9 Lead time reduction

Lean production aims, in particular, at reducing production lead times and costs (Marodin et al., 2017; Negrão et al. 2019; Nawanir et al. 2010). Reducing lead time is an essential result of an effective lean system (Nawanir et al. 2020).

The matter of lead time reduction is of great importance in competitively priced markets, as it is the key driver for profitability, but people are less aware of lean production and its possible influence to cut down on lead time, which can dramatically enhance operations and management systems.

The time it takes for the product to be delivered after the customer places the order is the so-called lead time for delivery. This covers the time required for the purchase, transportation, and production of the materials and parts required for the finished product and the time required for the delivery of the material to the one who ordered it.

All activities contribute directly or indirectly to the lead time, whether unnecessary or not (e.g., see Sahoo, 2019). As a result, lean strategy such as JIT supplier, production, and customer involvement in waste reduction due to extended lead times is particularly significant (Negrao et al.2019). For example, the use of Kanban signals the right time to replenish supplies before they run out efficiently, tackling lead time. A company that produces a product with a very short lead time can attempt to maintain fewer finished items in order to meet client orders to mitigate waste from the excess stock effectively.

Understanding and recognizing the lead time of a facility is particularly significant in the use of just-in-time production or the practice of internal lean production, as both are interconnected. Lead time can be used together with other lean approaches such as value stream mapping. Using the VSM, the inventory can be counted at each step of the mapping process and worked with the lean team to find places that produce waste in order to simplify the process to eliminate unnecessary waiting times and inventory overflow.

Table 2 represents the operational metrics adopted in this study, and that was also used by other previous studies. The literature in some of these studies has been used to support the use of the same metrics in this study.

**Table 2: Operational metrics and the supporting LM literature**

| Operational metric | Some of LM literature where the dimension was used |
|---|---|
| Quality of the yields | Khanchanapong et al. 2014; Belekoukias et al. 2014; Taj et al 2011 |
| Manufacturing cost | Valente et al. 2020; Alsmadi et al 2012; Onofrei et al 2019 |
| Productivity | Rahman et al. 2010; Lassaad Lakhal 2020; Ghosh et al. 2013 |
| On time delivery | Sezen et al. 2011; Wickramasinghe et al 2016; Rahman et al. 2010 |
| First-pass yield | G.L.D. Wickramasinghe & Wickramasinghe 2017; Panwar et al 2017 |
| Elimination of waste | Panwar et al 2017; Zarinah et al. 2017 |
| Reduction in defects | Muhammad Y. Jibril 2019 |
| Lead time | Marodin et al. 2017; Negrão et al. 2019; Nawanir et al 2010 |
| Flexibility | Filho et al. 2016; Chavez et al 2013; Al-Zu'bi et al 2015 |

### 1.5 Internal lean manufacturing and operational performance

Internal lean manufacturing practices have been linked to increased operational performance time and again (e.g., see Shah and Ward 2003, 2007). Lean procedures are supposed to increase operational performance by streamlining processes and boosting process consistency, at least in theory. Lean bundles, according to (Shah and Ward 2007), contribute significantly to plant operating performance. To elaborate, some researchers argue that when lean methods are considered as a system, they benefit the entire organization (Womack & Jones, 1996). The central argument is that by reducing imperfections and inefficiencies in operational processes through the employment of the lean practices in complementarity and throughout, the firm's operational performance improvement will be the ultimate consequence.

Although firm performance in lean manufacturing is widely varying and very broad in scope depending on who defines it, there is general agreement that it should be defined in terms of different measurement contexts with comparisons such as non-operational (business) and operational measures; internal and external measures; and primary and secondary measures (e.g., see Alkhawaldeh & Alsmadi, 2006; Venkatraman & Ramanujam, 1986). This is due to the fact that firm performance may only provide a partial picture and indication of the business situation (Curkovic, Vickery, & Droge, 2000). The empirical validity of the influence of lean practices on business performance in the literature is still in its early stages, and academics and scholars are required to help advance it further.

Various research on the ILMP-OP relationship has found that lean manufacturing deployment has a significant positive impact on operational performance (e.g., see Cua et al., 2001; Shah and Ward, 2003). However, a recent analysis (Negro et al. 2017) attempts to balance this assertion, highlighting that a number of certain research found a negative correlation, particularly for lean practices such as JIT supplier delivery, Kaizen, single minute exchange of die (SMED), cellular manufacturing, VSM, and TPM. In a similar vein, Bevilacqua et al. (2017) discovered no link between lean bundles and firm performance. Another study (e.g., Sakakibara et al., 1997), for example, showed that there was insufficient data to suggest a substantial association between internal lean practices like set-up time reduction and operational performance. Similarly, while some internal lean manufacturing practices, such as reducing set-up time, were found to have a positive impact on operational performance, it was discovered that not all of the internal lean dimensions were very effective, contradicting some of the earlier studies that had established a strong link between some of the ILMPs and OP (Callen et al., 2000). The lack of consistency in the outcomes has been linked to the general complexity of the link between lean manufacturing processes and performance, which is still poorly understood and sometimes dismissed as insignificant (Swink et al., 2005).

The literature on lean production, on the other hand, suggests that implementing a bundle of lean production practices at the same time may result in higher levels of improvement in manufacturing plant performance by streamlining processes and thus increasing process consistency, stability, and accuracy (Birdi et al., 2008). Rising productivity levels, quality improvement, reduced lead times, and cost reduction are some of the benefits to the manufacturing plant resulting from the efficient adoption of lean production processes (Birdi et al., 2008; Karlsson & Åhlström, 1996). Another study (Panwar et al., 2018) found that adopting lean principles improves operational performance in areas including inventory management, timely delivery, waste reduction, demand management, cost reduction, and productivity enhancement.

Swamidass (1996); Sawhney and Chason (2005) found that implementing internal lean techniques improved product quality and reliability, unit manufacturing cost, timely delivery, labor productivity, and employee satisfaction to a great or significant amount.

According to research studies (Cua et al., 2001; Shah & Ward, 2003), the higher the degree of leanness, the larger the favorable benefits on operational performance for implementing firms.

This present study is concerned with the internal aspect of the lean manufacturing strategy. These internal lean practices are conceptualized as an integrated approach to the management of internally related operations of manufacturing systems, characterized by pull-production systems, statistical process control, total productive maintenance, reduced set-up time, and quality management, among others, with the goal of eliminating waste (see, e.g., Chavez et al. 2013; Chi Phan et al. 2019; Marodin et al. 2017).

## 1.6 Research model and hypotheses

Based on the objectives, the research model demonstrates;

i) Aggregate ILM against operational performance

ii) Each of the individual ILMP constructs against operational performance and

iii) How each of the three moderators, that is to say, firm size, industry type, and type of economy, affect the named relationships (i) and (ii), is developed (see figure 5).

Operational performance is broad, and in this particular research, it has been defined as consisting of dimensions like lead time, quality, cost, productivity, delivery, through pass yield, flexibility, waste minimization, and reduction of defects.

Hypothesis development

We have three main hypotheses, as listed earlier. And from these major hypotheses, 24 other secondary hypotheses have been derived.

H1: Aggregate internal lean manufacturing implementation positively and significantly influences the operational performance

H2: Each of the six practices/constructs under ILM positively and significantly influences the operational performance

We then test moderators on each of the relationships (H1 and H2) above to ascertain they are influenced by the presence of moderating factors, i.e.;

H3: Aggregate ILMPs and each of the individual ILMPs are positively and significantly influenced by moderator variables

To expound further on hypothesis two;

H2a: Implementing statistical process control positively and significantly influences the operational performance

H2b: Implementing total productive maintenance positively and significantly influences the operational performance

H2c: Implementing setup time reduction positively and significantly influences the operational performance

H2d: Implementing employee involvement positively and significantly influences the operational performance

H2e: Implementing continuous flow production positively and significantly influences the operational performance

H2f: Implementing pull production positively and significantly influences the operational performance

Hypothesis 3 has 21 more hypotheses that have been derived from it. Since we have three moderating factors, each moderating factor is tested against each of the relationships above.

Therefore;

H3: The relationship between ILMP and operational performance is positively and significantly influenced by moderating factors

H3a: The relationship between statistical process control (SPC) and operational performance is positively and significantly influenced by moderating factors

H3b: The relationship between total productive maintenance and operational performance is positively and significantly influenced by moderating factors

H3c: The relationship between pull production and operational performance is positively and significantly influenced by moderating factors

H3d: The relationship between employee involvement and operational performance is positively and significantly influenced by moderating factors

H3e: The relationship between setup time reduction and operational performance is positively and significantly influenced by moderating factors

H3f: The relationship between continuous flow production and operational performance is positively and significantly influenced by moderating factors

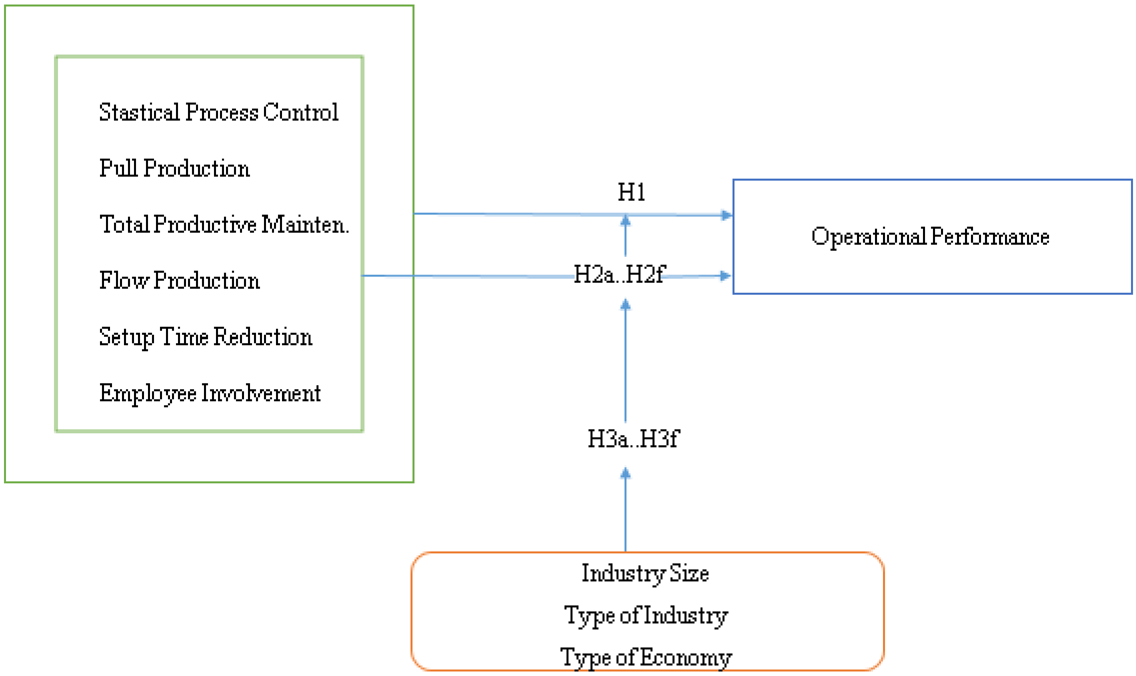


**Figure 5:** The research model

### 1.7 Summary of the chapter

The literature attempts to collect notes and gain insight from earlier theoretical and quantitative investigations analyzing the link between lean production and performance. A metadata review is built from this research to synthesize these investigations in order to produce a general outcome of the investigated relationship.

In this chapter, detailed literature on lean definition is presented, its evolution and implementation, the definition of lean, the internal lean manufacturing practices, the ILMP- operational performance relationship, operational metrics hypothesis development, and the research model are contained herein.

Each of the six practices under internal lean manufacturing has also been thoroughly discussed, that is to say, total productive maintenance, statistical process control, pull production, flow production, setup time reduction, and employee involvement. From Shah and Ward (2007), one of the widely used proposed models in the field of lean manufacturing, these six constructs were adopted.

The dependent variable operational performance has also been thoroughly discussed and narrowed in the scope of nine metrics, namely lead time reduction, quality of the output, cost of manufacturing, productivity, on-time delivery, through pass yield, production flexibility, waste minimization, and reduction of defects.

The research framework consists of the three major hypotheses

i) Aggregate ILMP- operational performance relationship

ii) Each of the six practices of ILM against operational performance and

iii) How each of the three moderating factors affects each of the two relationships (i) and (ii)

# CHAPTER 2: RESEARCH METHODOLOGY

## 2.1 Introduction

This quantitative study was conducted to examine the connection between internal lean production processes and operational performance. A meta-analysis approach for synthesizing the results of distinct but related research across eleven years from 2010 to 2020 has been taken to assess the extent of the ILMP implementation in OP.

This chapter, therefore, presents discussions of the methodology and research design, a detailed explanation of sampling and sampling procedures, the statistical software used as well as data analysis.

## 2.2 Research design and rationale

A comprehensive quantitative meta-analysis was adopted so as to establish the impact of ILMP implementation on OP. In a subject with inconsistent results and wide-ranging ILM practices and operational performance, a meta-analysis approach to try to compare all the studies done on the ILMP-OP becomes very important. This ILMP- operational performance study has been conducted in a perspective of ascertaining the aggregate ILMP impact on operational performance, then the impact of different constructs under ILM on operational performance, and then subjecting these two associations on moderating factors to better understand how each of the relationships is impacted in particular situations. That is in regards to the size of the firm, type of the industry, and the type of economy or level of economic development in which the chosen sample falls. Although most of the studies have come up with positive and significant results, the impact of the different constructs or the dimensions of ILM on operational performance varies in the degree of impact. Some ILM constructs show a stronger impact, others a lesser impact, and others a non-significant or negative impact on OP. A quantitative meta-analytic design has the ability to address these issues and test for the effects of moderator variables. However, in order to effectively address the aforementioned scenarios, hypotheses development, and research that enrich the ILMP- operational performance literature mixed approach was adopted. Hunter and Schmidt (2004) explain that meta-analysis of correlation is a methodology that provides a deeper understanding of a phenomenon through the description of the independent and dependent variables.

Meta-analysis is not only an objective and quantitative technique through which empirical studies on a topic with inconsistent or vague results can be statistically integrated or aggregated to assess their effect sizes in the field of psychometrics. It has also been used in lean manufacturing researches (e.g., see Abru-Ledon et al.,2018), product innovation (e.g., Sharma, 2015), total quality management (e.g., see Muhammad Y.J, 2019), supply chain integration (e.g., see Singini, 2020) and many other subjects.

The methodology is widely regarded as an essential component of scientific research and theory formulation (Rosenthal & Rosnow, 1991; Hunter & Schmidt, 2004). And because of this, meta-analysis was thus adopted as the statistical technique to identify, aggregate, and give a brief and general view of the findings of ILMP- operational performance association using studies collected in the last 11 years beginning from 2010 to 2020.

### 2.3 Sample and sampling procedure

Sampling is a procedure or way to select from a certain population a representative set of individuals or cases. In cases for which information is not easily obtainable from every individual/character, for instance, in biology or psychoanalytical, industrial quality control, or sociological surveys, sampling is appropriate to be used (see Ross and Westfall, 2020). A sample is a portion of the entire group (called a population) that is picked out to be subjected to tests, and then results are taken to generalise the rest of the population.

It is for this reason that sampling is as important as the sample in any study. It is believed that the sampling technique adopted greatly influences the generalizability of findings based on the sample.

Generally, the two major techniques that are mostly employed to draw a sample from a population are probability and non-probability sampling. But for the purpose of this meta-analytical study, a three-stage literature review was conducted to constitute the sample.

#### 2.3.1 Stage 1: Search for literature

The first stage towards gathering primary studies (both published and unpublished) to constitute the sample for this meta-analytical study mainly involved a two-step extensive literature search: computerized database search and manual search (offline) of existing literature.

### 2.3.2 Computerised database search

Green, Johnson, and Adams (2006) reiterated that electronic databases offer the most effective approach for searching and acquiring literature. Therefore, from the Sakarya university E-Library resource, a comprehensive search of the most prominent and widely used databases in the field of production, industrial engineering, manufacturing, operations, and business was conducted. Some of the databases accessed for published articles and dissertations were JSTOR, ABI/INFORM, Google scholar, Sustainability, Emerald Insight, ScienceDirect, EBSCOhost, Taylor & Francis Online, ProQuest, Researchgate, and Springer. These databases are the most frequently used to identify prospective relevant studies needed to undertake meta-analysis (e.g., see Leuschner, Charvet & Roger, 2013). They also include the greatest archive of published journal articles and all together constitute an integral source of empirical investigations.

The search was done with the combined following keywords: “lean manufacturing,” “LM,” “Internal lean manufacturing practices,” “lean principles,” and “firm performance,” “operational performance,” “organizational performance,” and “business performance.”

### 2.3.3 Manual search

Although the computerized search produced several articles and dissertations, a manual review of the bibliographies of most of the published studies was done to find out studies that could not be found through the computerized search. To ensure that there is no “file drawer problem” where 5% of the studies in journals may contain Type 1 errors coupled with the realization that nearly all of the studies in the lab’s file drawers are non-significant (e.g., Rosenthal 1984), a comprehensive search for unpublished studies including articles and dissertations was conducted on the ProQuest and EBSCO search engines. Also, offline searches for LM literature material in textbooks, directories, and the Sakarya university library were done. This was to ensure that the results of this meta-analysis were free from distortions due to the absence of unreported and observed effect sizes (see Lipsey & Wilson, 2001). This is a very important step since a meta-analysis with a portion of the population intentionally left out is considered incomplete or inadequate to give a general result of the whole of the studies in a selected sample (Hunter and Schmidt 2004).

### 2.3.4 Stage 2: Inclusion and exclusion criteria

In the quest for the search for studies, there were many hundreds of them that were returned. However, just between 30-50 studies made it to the second last and final stage of adoption for this particular research. Therefore, in order to ensure that relevant primary studies were selected and that only those with all the outlined characteristics were finally included in the analysis, the following inclusion and exclusion criteria were used:

- Only quantitative or empirical studies
- ILMP-operational performance linking analysis articles
- The effect size of the ILMP-operational performance link is assessed by Pearson's correlation coefficients or similar approaches.
- The ILMP or any measure of LP and at least one measure of its operational performance was empirically analyzed.
- Only English papers from any country or region
- Published within the time frame 2010- 2020
- Focussed on only manufacturing companies
- Defined operational performance as strictly having one or more of the dimensions including waste minimization, product quality, manufacturing cost, defects reduction, productivity, speedy delivery, flexibility, first-pass yield, and lead time reduction.

### 2.3.5 Search results

In the preliminary stage of the literature search using terms such as “lean manufacturing,” “internal lean practices,” “lean,” “operational performance,” and “firm performance” in databases such as Taylor and Francis, Google scholar, Emerald Insight, ScienceDirect, EBSCO, ProQuest, ResearchersGate, etc., produced a total of 605 published and unpublished articles considered as empirical and quantitative for the period 2010 to 2020.

The search and review of the bibliographies of some studies manually (offline) produced five (5) more studies hence a total of 605 studies altogether.

By thoroughly examining the abstracts of the gathered studies, it was determined if each of the studies was examining the impact of ILMP implementation on operational performance and if all the keys in the inclusion criteria were met.

And for further clarity, perusing through the methodology and results section of these studies reaffirmed the inclusion of the study, and if deviations or discrepancies were noticed, then the studies were excluded.

This exercise alone got 501 studies eliminated that had not met all the eight keys of the inclusion criteria or had reported insufficient data needed to compute the effect sizes. In some cases, the original authors were contacted to help retrieve any missing info or make clarifications on their studies which were required so as to capture the real gist of these studies and their author's real intent. For instance, JIT, TQM, HRM are broad terms within LM. In some instances, the authors had not specified or broken down these terms into their respective practices so as to understand what practices or principles they were actually alluding to.

Unfortunately, by the time of compiling this report, none of them had responded, and as a result, five additional studies were dropped.

### 2.3.6 Stage 3: Final selection

Now left with ninety-nine (99) studies, these were wholly perused to establish their suitability for this research.

Some of these studies had general terms like lean manufacturing and operational performance, of which the underlying constructs were not specifically defined, or those constructs and dimensions under consideration were out of the inclusion criteria of this research. Twenty of such articles had to be expunged.

Likewise, it was found out that some of these studies had mixed sectors of both manufacturing and service sectors. Because the research only takes into account firms that are 100% manufacturing, a further twenty-nine (29) studies were dropped.

For the remaining fifty (50) studies, these were all taken, and they all contributed to this research in writing the introduction and literature review. However, for the meta-analysis computations, only thirty studies were used. This was so because the other twenty (20) studies were relevant but reported neither by Pearson correlation coefficient nor by other related test statistics about the effect size for the ILMP- operational performance relationship like the beta, which could be converted to Pearson correlation.

Therefore to this end, a final thirty (30) studies were used in the meta-analysis computations fulfilling all the eight keys of the inclusion criteria. This number of studies is acceptable to carry out a meta-analytic study (see Nair, 2006).

The steps of the sampling procedure are presented in Appendix 1. So, for this meta-analysis, 30 studies with 30 effect sizes and an aggregate sample size of N=7,075 were considered.

Below is the flow process for the search and final selection of the studies included in the meta-analysis study.

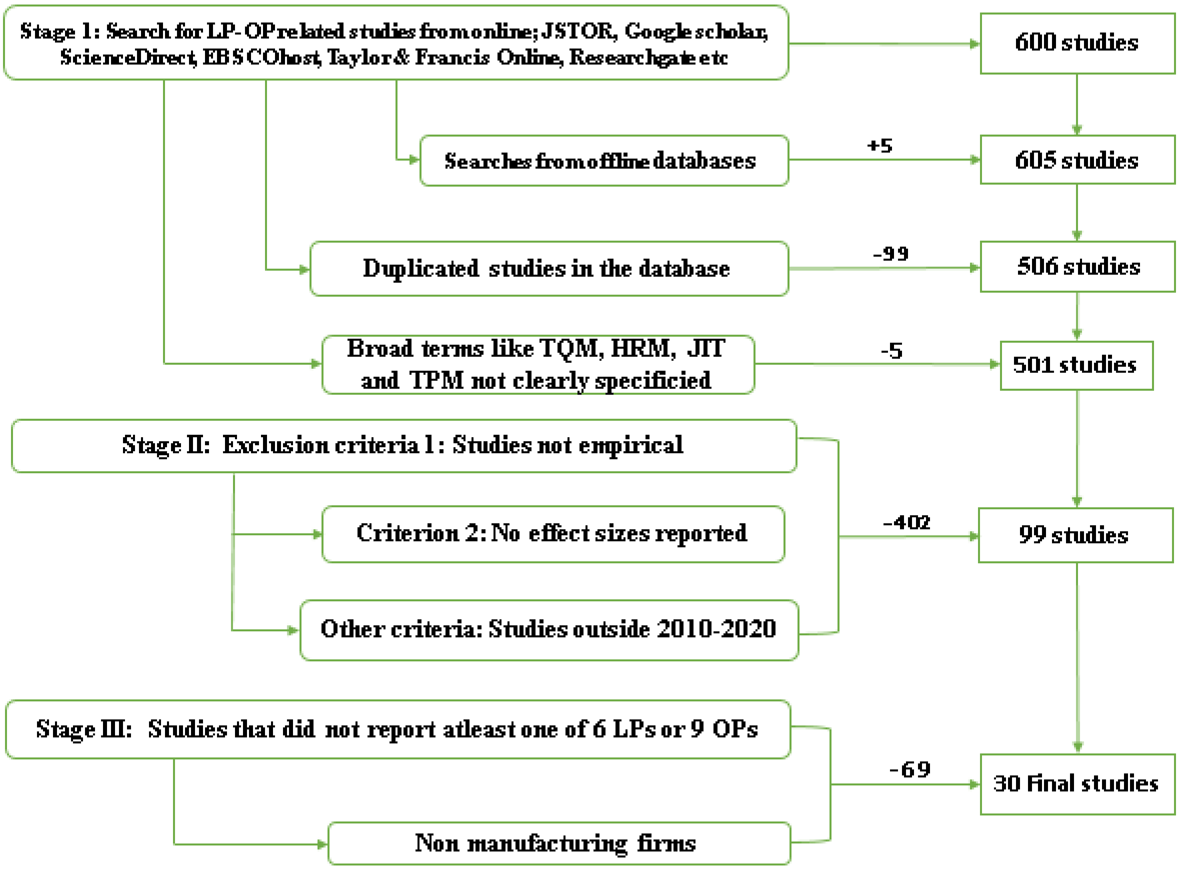


**Figure 6: Paper selection process**

### 2.4 Coding of the studies

Coding is a very important yet tedious aspect of meta-analysis. It involves extracting from the selected studies important data based on the inclusion criteria, organizing this data to make meta-analysis computations, and for the analysis and interpretation of the organized data.

It enables different attributes and characteristics or figures to be extracted from the studies. A three-pronged approach of coding was used, namely designing the coding form, establishment of coding instructions, and the determination of reliability of the coded results

### 2.4.1 Designing a coding form

A Microsoft word form was used for the coding process to extract basic qualitative information of the studies. Coded fields included: authors' last name, publication year, journal name; sample size; country; statistical analysis method, and the dimensions and constructs of both ILM and operational performance. (See Appendix 2)

### 2.4.2 Coding information

For each study, a number of columns representing pieces of information were retrieved using the coding form. The retrieved information was generally categorized into three; study identification, sample characteristics, and outcome characteristics. The study identification category basically highlights the author's last name, year of publication, and journal of publication.

For the coding process, for the calculation of effect sizes, and for conducting any moderation analyses required, the excel spreadsheet was used. The fields coded included: author; year; type of industry sector; sample size; country; methodology of statistical analysis; abstract; primary study findings; used scales; scale reliability, among other items. The kind of economy (or degree of economic development) of the country where the firms were selected was among the coded variables for potential testing as a moderating factor. The economies of the countries were either (1) advanced economies, (2) emerging market/developing economies, based on IMF (2016) statistics, or categorization

In accordance with the correlation meta-analysis technique, the three key information pieces noted from the study were the sample size, the reliability figures of the dependent and independent variables, and effect sizes assessing the ILM-OP relationship.

In some circumstances where the authors could not ascertain the reliabilities of particular variables or where these reliabilities were deemed missing, the average reliability computed across the different studies was used as a replacement (see examples by Demirbag et al., 2006; Panuwatwanich & Nguyen, 2017).

The outcome characteristics category then moves further to provide an in-depth description of the ILM practices and the operational performance dimensions considered in the study.

### 2.4.3 Coding instructions

To achieve strict adherence to the coding process, a set of clear and concise instructions was formulated to help guide the coding process. It provided a detailed description of all the relevant data needed for the meta-analysis and the mode of extraction of this data from every study. This was meant to avoid any ambiguities and achieve precise and clear results of the coding process in a uniform and detailed manner. (See Appendix 3)

### 2.4.4 Coding reliability

To ensure against any slight errors that may be made in the course of the coding process, the Jamovi meta-analysis meant for systematic and meta computations was used. All the necessary coding reliability tests, as well as the coding for this study, were done with the help of Excel and Jamovi statistical software.

Rigorous cross-checking by the author was done numerous times by making use of the meta-analysis tools, Microsoft Excel, Microsoft Word, and the software. The ten columns of information were tried in two separate sheets, tools and software, and compared to each other to ascertain if they were in agreement. No discrepancies were realized.

The same work was given to a second researcher to independently review it so as to ensure consistency. The outcome of this was a 98.8% consistency with the results by this researcher.

## 2.5 Effect size conversion and estimation

All the effect sizes used in this study were converted into Pearson correlation coefficients with the help of Hunter and Schmidt's (2004) formula and Wilson's effect size calculator. According to Schmidt and Hunter (2004), Leuschner et al. (2013), Mackelprang et al. (2014) and it is advisable that effect sizes for a meta-analysis correlation be in Pearson's correlation, r.

The meta-analysis is used to compute effect sizes from various quantitative data and can convert these data to any desired metric (r) courtesy of the Psychometrica (2018) and the

Wilson (2016) effect-size calculators. After the coding procedure and the conversion to a uniform metric r, then the meta-analysis was drawn based on disattenuated correlations.

Correlation coefficients were established between all possible aggregated internal lean practices and each of the individual internal lean practices and operational performance metrics to determine interdependencies between internal lean practices and operational performance benchmarks.

The Cronbach alpha was considered as the reliability estimate for the ILM constructs. Where the researchers could not find the reliability of some particular studies, average reliability provided across all of the research was used as an alternative (e.g., see Bamberger et al., 1999; Kinicki et al., 2002; Mackelprang and Nair, 2010).

### 2.6 Averaging correlations within studies

Some research studies were observed to have reported more than one correlation. Before these studies were synthesized, the correlations were aggregated into a single average effect size. In general, several correlations were reported in a single study because of the various ILMP or operational performance metrics deployed, or both.

In meta-analyses, it is a normal place to synthesize effect sizes on the basis of different independent or independent variables (e.g., Kirca et al., 2011; Rosenbusch et al., 2011). The argument to average numerous correlations reporting on a single variable based on separate but conceptually comparable measures reported in a single study is supported by this approach. Lipsey and Wilson (2001) emphasize this technique and its appropriateness by ensuring that the conventional manner in which numerous effect sizes are handled is to choose a single effect size from a number of them or achieve an average correlation and to input the single average value.

(Credit: Sharma, 2015)

### 2.7 Aggregating correlations across studies

The systematic grouping of the disattenuated effect sizes, i.e., correlations that have been adjusted for artifacts, which is frequently used in descriptive statistics, is the summary population correlation similar to the weighted mean (Borenstein et al., 2009).

Fisher's Z transformation and Schmidt & Schmidt (2004) are the most often used methods to obtain the summary effect size (see Borenstein et al., 2009). The Schmidt and Hunter technique proposes the calculation of summary effects on correlations directly.

From the excel sheet prepared, the summary correlation was computed as;

$$\text{Population correlation, } r = \frac{\text{The sum of corrected correlation weights (cctd r W)}}{\text{The sum of the weight of studies (W)}}$$

## 2.8 Interpretation of effect sizes

Interpretation of effect sizes is essential to quantitative research. Thus, standards for interpreting meta-analysis effect sizes were adopted to provide logic and meaningful understanding. Specifically, Cohen (1992)'s effect size standards were appropriate for interpreting effect sizes. For instance, he classified effect sizes (r) into small (i.e. below 0.10), medium (i.e. between 0.3 & 0.50), and large (i.e. above 0.5). Lipsey, on the other hand, categorized effect sizes into small, medium, and large effects based on the ranges, i.e., effect sizes below 0.32 are interpreted as a small effect, the medium effect is 0.32 – 0.55, and effect sizes greater than 0.55 are interpreted as a large effect.

Thus, the interpretation of the magnitude of every effect size in this study was based on Cohen's (1992) standards.

## 2.9 Data analysis

Like many meta-analytical studies, this one follows the usual steps such as study selection, coding, and the conversion of effect sizes into the appropriate statistics. The choosing of a suitable model for the study is another important step in the meta-analysis process. Due to the heterogeneous or diversified nature of the study samples, a random-effect model was chosen over the fixed-effect model. Schmidt and Hunter (2004) recommended that the fixed-effect model be used when all the studies under analysis are homogeneous across population effect sizes. But where the population parameters vary from study to study, the random-effect model should be used to conduct significance tests and confidence intervals.

## 2.10 Statistical artifacts

Artifacts generally attenuate the outcomes of the studies, which implies that they reduce the value of effect sizes (Borenstein et al., 2009). Thus in order to estimate the disattenuated (i.e., artifact-corrected) correlations, the artifact-based correction methodology suggested by Hunter and Schmidt (1990) is used. The disattenuated correlations were larger in magnitude, as is the case in all meta-analyses than the reported initial (attenuated) correlations, as is characteristically the case for all meta-analyses.

Artifacts are errors in the primary studies that arise from study imperfections and, therefore, must be corrected using statistical information (Schmidt and Hunter (2004).

Schmidt and Hunter (2004) identified 11 different artifacts that need to be given much attention in any meta-analytic study. But for this particular study, two major artifacts; sampling error and error of measurement, were the only ones taken into consideration according to the available information.

### 2.10.1 Sampling error

Sampling error can occur when a sample selected from a bigger population group falls short of giving the general representation of the whole data population. This can lead to findings in the sample that do not exactly represent the results from the overall population (see, for example, Ross and Westfall, 2020).

Sampling error is the most damaging artifact in narrative reviews (Schmidt and Hunter 2014). The size of the sample of any given study determines how accurate it can represent the study population. Thus, a randomized sample selection and/or more observations made can be applied to lower a sampling error (Ross and Westfall, 2020).

In line with the recommendation of Schmidt and Hunter (2014), sampling error was corrected in this meta-analysis by weighing the study findings by their sample sizes. This was done by calculating a weighted effect size for every study so that studies contribute to the meta-analysis conclusion based on their respective sample sizes. The Jamovi software was used in this case.

### 2.10.2 Measurement error

Measurement error, as the second artifact that needed covering in the study, was done through the help of a reliability formula shown below. Measurement error is inversely proportional to reliability. This simply means that the higher the reliability coefficient, the less measurement error and vice versa. Variations in terms of measurement and the corresponding measurement errors usually affect the size of the correlations in primary studies. This may lead to attenuation of the relationship between ILM and operational performance. To correct this attenuation, reliability information of ILM and/or OP constructs were used.

The Schmidt and Hunter's reliability formula, which is especially suited for Pearson product-moment correlation effect size, was adopted to obtain reliability measures where the study did not provide for them.

The formula is stated as;

$$\mathbf{r}'_{xy} = \frac{\mathbf{rxy}}{\sqrt{r_{xx} \cdot r_{yy}}}$$

Where; $r_{xy}\,'$ is the corrected, weighted correlation coefficient; $rxy$ is the uncorrected, unweighted correlation coefficient; $r_{xx}$ is the reliability for ILMP, and $r_{yy}$ is the reliability for operational performance.

### 2.11 Heterogeneity analysis

The random-effect model, held under the assumption that the true effects are normally distributed, requires testing for heterogeneity. To test for the presence of heterogeneity in the study as well as assess the presence and effects of moderators on the relationship under study, heterogeneity analysis was thus carried out.

From the many available methods for testing heterogeneity, the Q statistic and $I^2$ index were found suitable for this review. A significant Q statistic, according to Borenstein et al., 2009, may signal the presence of moderating factors. On the other hand, the $I^2$ index, according to Higgins et al. (2002), reveals the strength or degree of heterogeneity. Unless coupled with the $I^2$, a significant Q statistic does not tell us much about the size of heterogeneity. It is $I^2$ which could be classified as low, moderate, and high that tells a lot about heterogeneity. For instance, $I^2$ of 25 percent could be said to represent low heterogeneity. Whereas that of 50 percent could represent, a moderate and 75% and over could represent a high heterogeneity (Borenstein et al. 2009). However, this depends on the interpretation standards adopted in any study.

### 2.12 Moderator analysis

One unique advantage of meta-analytical evaluations over narrative reviews such as systematic reviews is their ability to assess the effects of moderators on the association under scrutiny (Aguinis et al., 2011).

The use of moderator factors is among the unique features and key tenets of meta-analyses, as moderators help to define the boundary conditions of a theory (Aguinis et al., 2011; Viswesvaran & Ones, 1995).

The Schmidt and Hunter's 75% rule and the Hedges and Olkin procedures are some of the two major methodologies utilized for detecting the presence of moderator variables. According to (Hunter and Schmidt, 1990), a 75% threshold for examination of the variance in correlations can be employed for the detection of moderators.

The Hedges and Olkin approach is used to analyze whether the variance in effect size can only be attributable to or not to a sample error (Borenstein et al., 2009). When the X-squared (chi-square) value is statistically significant, it becomes crucial to examine potential moderators (Kirca et al., 2005).

The Hunter 75 rule was chosen for this particular study as it was deemed simple and doable by the available Jamovi software that was used.

Moderators, though not entirely, may account for variability in effect size estimates across studies. The ILMP- operational association in the literature, as seen in the hypotheses development section above, may be subjected to a number of moderators. It is in the interest of this study to assess the effects of these moderators and determine their significance to the ILMP-operational relationship. A more detailed discussion on the moderator's analysis is further discussed in the subsequent chapters.

(Credit: Sharma, 2015)

### 2.13 Moderator variables

It is vital for the theory development to establish the moderation effects of a relationship (Viswesvaran & Ones, 1995). A moderator is a factor or variable that helps determine the degree or direction of the association between the independent and the dependent variables (Aguinis & Pierce, 1998). In other words, the strength and direction of the link between two variables would vary according to the degree or extent of the effect of the moderator to which it was subjected to. An assessment of the theoretical reasons in the literature of the research should be used to identify the moderators (Geyskens et al., 2009).

The two most followed approaches used in meta-analysis based researches for identifying moderators and establishing their impact are:

i) Hypothesize potential moderator factors prior to data analysis and

ii) Test for moderation effects without postulated moderator variables (Borenstein et al. 2009). The meta-analytic study done by Gonçalves et al. (2019) followed this approach.

This study adopted the first approach as shown, i.e., it developed the hypotheses prior to conducting the data analysis (heterogeneity analysis).

**Table 3: Some of the moderator variables adopted by previous studies**

| Level | Potential moderating (or contextual) variables | Examples of studies |
|---|---|---|
| **Lean implementation** | Different bundles of practices | Danese et al. (2012) |
| | Time that practices have been in use | Agus and Iteng (2013) |
| **Plant** | Plant age | Shah and Ward (2003), Danese et al. (2012) |
| | Plant size | Shah and Ward (2003) |
| | Unionization | Shah and Ward (2003) |
| **Company** | Geographical location (national culture and development level) | Moyano-Fuentes and Sacristán-Díaz (2012), Kull et al 2014 |
| | Organisational structure | Rahman et al. 2010 |
| | Organisational culture | Pakdil and Leonard 2015 |
| | Company size | |
| | | Agus and Iteng (2013), Khanchanapong et al 2014 |
| **Industry** | Sector | Danese et al. (2012, Eroglu and Hofer 2011 |
| | Competitive intensity | Azadegan et al. 2013 |
| | Environmental uncertainty | Azadegan et al. 2013, Chavez et al 2015 |
| **Industry** | Cross-functional product design | (Saumyaranjan Sahoo and Sudhir Yadav 2017) |
| | Process quality management | |
| | Quality empowerment | |
| | Organization-wide employee training | |
| | Quality information usage | |
| **Supply Chain** | Power within the supply chain | |
| | Relationship with suppliers and customers | |
| | Communication network | |

**Credit:** Mackelprang and Nair (2010); Abru-Ledon et al (2018)

For this particular study, the moderator variables chosen to test the two primary and the twenty-four (24) secondary relationships of the ILMP- operational performance were firm size, industry type, and the type of economy.

### 2.13.1 Firm size

Average sales revenue of sampled companies is one of the most common yardsticks for determining the company's size (e.g., Drnevich & Kriaučiūnas, 2011; Grawe et al. 2009) and the average number of active employees in a company (e.g., see Atuahene-Gima, 2005; Danneels, 2012).

The three categories of sizes included in this analysis are the small, medium, and large size enterprises.

Firms based on how large or small they are largely impacting the operations within the firm and, as a consequence impact the implementation of lean manufacturing. To distinguish small and medium-sized enterprises from large companies, a host of benchmarks have been introduced in the literature as there is no general rule of thumb for such classification. (Rosenbusch et al., 2011).

The key variables deciding whether the company is a SME or an LE are employee headcount and turnover or the whole balance sheet, according to the classification of the European Union. Small and medium enterprises have a staff headcount of 50 and less individuals, while medium enterprises have a threshold of 50 up to 250 employees. The large enterprises comprise more than 250 according to the benchmarks set by the European Union Commission Internal Market, Industry, Entrepreneurship and SMEs.

However, it is different in the US where the difference between large and small enterprises is at the threshold of 500 employees and less or more. This yardstick has also found application in a number of research works.

However, the criterion adopted in this research is the same as that of the Economic Co-operation and Development Organization (OECD) which defines the firm size according to employee staffing, i.e., a small enterprise has $\leq$100 employees, a medium one has 100-250 employees, and a large enterprise consists of 250 up to 1000 employees.

With the varying sizes comes challenges or even ease of the application of lean manufacturing. For example, SMEs are labeled as having higher agility and flexibility than their larger counterparts (see, e.g., Damanpour, 1996; Verhees & Meulenberg, 2004). This may give SMEs an advantage over the LEs despite resource constraints to yield successful performance outcomes, especially employee satisfaction due to well-enforced employee participation, reduced defects in the process because of adequate process monitoring, and reduced inventory and manufacturing costs if pull production is well implemented.

Conversely, large firms can gain inertia that may come with the increase in their size, which might prevent them from responding as promptly as possible to the changing conditions around them (Boeker, 1997). Also, large companies are expected to be more specialized and sophisticated in their procedures (Krasnikov & Jayachandran, 2008). Peculiarities or idiosyncrasies in large enterprises reflect the distinctive nature of organizational structures, routines, and processes that make competing companies potentially very inimitable (Sharma, 2015). In addition to these, large enterprises enjoy economies of scale, which enable them to marshal large quantities of resources that can make it possible for them to hire consultants and experts, employ sophisticated operational tools and adopt a policy in line with the implementation of an organization-wide lean framework.

In agreement with this are (Damanpour 1992; Schilke, 2014), who corroborated that large firms are expected to be endowed with a bigger resource base, and they can deploy a large number of such resources towards R&D (Scherer 1982: 234). They also usually have slack resources on hand as opposed to the smaller firms (Ettlie and Rubenstein 1987). Slack resources are excess resources beyond the minimum operating needs of a company required to achieve the required levels of performance (Nohria & Gulati 1996). Therefore, these can be pivotal advantages accrued to larger firms over their smaller counterparts, and hence they aid in the facilitation of the implementation of ILM.

### 2.13.2 Industry type

In various meta-analyses examining the topic of operations management, the effect of the industry type on several relevant associations has been explored (e.g., see Kirca et al., 2005). Manufacturing and service sectors in industries have frequently been categorized according to the nature of the commodities or services that the company produces and offers to end-users (e.g., see Muhammad, Y.J. 2019; Abru-Ledon et al. 2018).

According to (Abdulmalek, Rajgopal, and Needy, 2006), the discrete-type industries deal with items manufactured into individual units from smaller pre-fitted and already-made parts. Products made from discrete manufacturing include electronics, automotive, mobile phones, computers, and others, while process-type industries out products that undergo specific refining processes during production, i.e., chemical reactions, mixing, baking, and so on and in their physical and final form, they cannot be separated or converted back into their original form or parts.

Abdulmalek et al. (2006) and Dunstan, Lavin, and Sanford (2006) established that LM techniques equally and highly impacted both process type and discrete type industries. Though some researchers doubted the appropriateness of implementing lean in the industry settings different from that of the Japanese automobile industry (e.g., see Jorgensen and Emmitt 2008; Pettersen 2009), others, for example, Lyons et al. (2013), determined that lean practices, i.e., setup reduction, 5S, TPM associated with waste reduction were consistently applied for the improvement of the performance of process industries

Studies on the effect of industry type on lean manufacturing and firm performance relationship have largely found a positive correlation (e.g., Abru-ledon et al., 2018; Sezen et al., 2013; Sharma, 2015) with the exception of the few which have found a statistically non-significant result (e.g., see Vicent et al. 2004).

The different types of production processes, assembly lines, the nature of raw materials used, the type of machinery, etc., bring various techniques to apply to lean implementation. For instance, it would be near challenging to apply lean in mass production as opposed to batch and continuous production. As regards this research, industries have been categorized as either processing or discrete manufacturing firms. In both of these categories, each and every lean practice is expected to impact the performance outcomes of the manufacturing process or the production floor operations differently.

For process manufacturing firms, according to the Institute of Industrial and Systems Engineers (IISE), process industries are those in which the principal manufacturing operations are either continuous or occur on an identical batch of materials. It is associated with formulae and production recipes, ingredients, and bulk materials. In processing, the common methods used are grinding, mixing, blending, filling, purification, distillation, and others. Processing methods are also a form of non-reversible chemical and physical processes.

In a study by Lyons (2013), it was determined that lean practices, for example, setup reduction, 5S, TPM associated with waste reduction, were consistently applied for the improvement of the performance of process industries.

Some of the examples of processing industries in the sample of this study are textile and apparel, tobacco, rubber, petroleum, plastics, wood and wood products, chemicals, ceramics, plastics, food, beverages, pharmaceuticals, base metals, coal, textiles, paper and paper products and many others.

In the discrete manufacturing firms: here, it involves assembling parts or components and making things that are distinct. Most discrete manufacturing has a multi-step assembly process. If a single part or subassembly is missing, the whole production process will have to stop. The Assembly process also requires multiple machines, usually organized in cells (cellular network), parts located nearby for ease of access, ample factory floor space, and more human input or labor all throughout the process. Discrete manufacturers produce products that can be counted, itemized , and often require assemblage.

This type of manufacturing uses a bill of materials (BOMs) and assembles components along with routing. In light of this, it includes production methods such as make-to-order, assemble-to-order, engineer-to-order, and make-to-stock.

The final products under discrete are physical components. The parts used in assembly or manufacturing can be broken down and disposed of or recycled after production. It also applies assembly in a linear or routing way. Manufacturing stages in discrete can be joining, attaching, fixing, assembling, and the products cannot change in volume or density.

A number of studies have concluded that lean primarily find application in high volume, low variety discrete type of industries (e.g., see Liker 1997; Oliver, Delbridge, and Lowe 1996). In fact, many researchers doubted the appropriateness of implementing lean in another industry setting different from that of the Japanese automobile industry, especially Toyota (see, for example, Jorgensen and Emmit 2008; Pattersen 2009)

Automobiles, electronics and computers, consumer products, aerospace, aviation and defense, manufacturing and heavy equipment, and so on are examples of such industries.

Abdulmalek, Rajgopal, and Needy, (2006) list in Table 4 below some comparisons between discrete and process industries.

**Table 4: Discrete vs. Process industry**

| Discrete-type manufacturing | Process- type industry |
|---|---|
| Items | Material |
| Variable volume | High volume |
| Extended variety | Low variety |
| Flexible equipment | Dedicated equipment |
| Reduced setup times | Lengthy Setup times |
| Cellular/product lay outs | Fixed layouts |
| Parallel machines | Fixed routing |

**Credit**: Huq and Mitrogogos (2018). Impact of lean manufacturing on process industries; Blekinge Institute of Technology, Karlskrona Sweden.

### 2.13.3 Type of economy

According to an IMF (2016) statistical report, countries were classified into two economies. Under this meta-analysis, just as it is from this report, the same types have been considered, namely the developed and emerging market economies. Normally in these economies are different countries. And in these countries, they differ in terms of the resources they allocate to lean manufacturing, the type and amount of labor they allocate to LM, the importance they attach to LM, the organizational culture towards LM, the skills and knowledge towards LM, and the awareness about LM. In each of these economies, unionization, company policy, government policy, level of technology use in manufacturing, etc., varies and hence the varying effect on LM (e.g., see Shah and Ward 2007). The extent of skilled labor also varies from one type of economy to the other. This research looks at these countries clustered under these two types of economies to ascertain the variation in the magnitude of the impact of lean implementation on the operational performance of the firms in these countries.

In advanced economies, the countries selected here are called developed countries. The developed country, often known as an industrialized country, has a mature and sophisticated economy, which is typically assessed by GDP and/or average income per person. Gross Domestic Product (GDP) per capita, a tally of all commodities and services generated in a country in a year, is one of the major measures of an advanced economy. However, there is no official GDP per capita threshold for the various countries. Some economists put this amount at $12,000 per person as the bare minimum for a developed economy, while others suggest that $25,000 is a good place to start. (See, for example, Liberto and Estevez, 2021)

The IMF classified thirty-nine (39) countries as developed economies as of 2016. The United States and Canada, most European countries in the western hemisphere, Japan and Singapore, South Korea, as well as Australia and New Zealand, among others.

Developed countries have superior physical, human, and technological infrastructure, as well as automated manufacturing and service industries. Citizens and workers residing in these countries have easy access to high-quality and cheaper health care and education. Therefore, even the means of production and the technology, information, and tools of production are very advanced. Modern artificial intelligence, cloud computing, augmented reality, and automation is all used in manufacturing done in advanced economic systems.

In emerging market economies, according to Investopedia, an emerging market economy is one in which a developing country's economy is becoming increasingly intertwined with global markets as it develops. Emerging market economies are ones that have some, but not all, of the characteristics of an advanced market economy. Higher liquidity in local debt and stock markets, home creation of contemporary financial and regulatory institutions, and increased trade volume, and foreign direct investment from multinationals are all signs that an emerging market economy is becoming more linked with the global economy.

In the (IMF 2016) report, the developing market economy is usually evolving from a low purchasing power parity, weak and inadequate infrastructure, stunted development, and a pre-industrial economy to a more contemporary, industrial economy with an improved standard of life. Brazil, Saudi Arabia, India, Pakistan, Mexico, Russia, and China are examples of notable emerging market economies. Therefore such factors are expected to have a bearing on the organizational culture of the workforce in business organizations, the extent of ease of business operations in such economies, the availability of resources, skilled labor, and capability to implement lean manufacturing. Therefore, whether the influence of the country’s level of economic development on the ILMP-OP relationship will be positive or negative is yet to be seen.

## 2.14 Outlier and sensitivity analysis

Outlier detection and assessment of their impact on findings of given research are often touted as a daunting and time-consuming task (Hunter & Schmidt, 2014), and an outlier and sensitivity analysis is strongly advised to determine the degree to which outliers in the study affect the final findings (e.g., Borenstein et al., 2009; Geyskens et al., 2009). Despite the fact that researchers value it, the vast majority of meta-analyses carried out in management and other disciplines do not include outlier and sensitivity assessments because of the aforementioned reason given by researchers (Geyskens et al., 2009).

The current study's outlier sensitivity analysis followed other meta-analysts recommendations for why it should be done and how to carry it out (e.g., Borenstein et al., 2009; Geyskens et al., 2009; Lipsey & Wilson, 2001).

The studies included a direct comparison of results obtained with the complete dataset and those obtained with the dataset that did not contain outliers. The top and bottom 5% of correlations (in terms of magnitude) were removed from the dataset, and a meta-analysis was done on the remaining correlations, as recommended by Tukey (1960) and Huber (1980).

Because there are thirty articles in this study, 10% of the effect sizes are to be recognized as outliers in the current dataset according to the outlier and sensitivity rules. As a result, the summary effect size generated by the complete dataset was compared to the summary effect size generated by removing the rounded off four correlations (i.e., ten percent of the dataset values) comprising two correlations (i.e., five percent) each from the top and bottom ends.

Other types of sensitivity analyses that involve comparing summary effect sizes include:

i. Comparing summary effect sizes obtained using RE and FE models;

ii. Comparing summary effect sizes obtained with and without measurement error corrections; and

iii. Comparing summary effect sizes with and without allowing adjustment factors to the separate correlations.

Experts in meta-analysis regard the aforementioned types of sensitivity analyses to be desirable (e.g., Cooper, 2010), although they were not used in this study.

(Credit: Sharma, 2015)

## 2.15 Meta-analysis

A meta-analysis, according to Hunter and Schimdt (2014), is a way to integrate the findings of dissimilar but linked analyses. The systematic identification, assessment, statistical synthesis, and interpretation of results from numerous research are all important aspects of carrying out a meta-analysis. It's useful in research that delves into the same issue or problem but comes up with various and antithetical (contradictory) results, making it difficult to generalize and evaluate the overall findings. Meta-analysis found its earlier and particularly widespread application in the realms of psychology, medicine, and epidemiology, where it was and is still frequently used to aggregate findings from observational research, inform policy choices, and assess the efficiency of psychological, epidemiological, and medical interventions.

By defining the distribution of realistic correlations between independent and dependent variables, the approach of meta-analysis of correlations provides insight (Hunter and Schmidt, 2004), and in the field of operations management, it has been found to be effective in delivering quantitative explanations or interpretations (Mackelprang and Nair, 2010). This method is often regarded as an essential component of social and/or scientific inquiry and theory development (Hunter and Schmidt, 2014; Rosenthal and Rosnow, 1991).

Card (2013) contends that the progress of scientific and social knowledge is built on the notion of reproducibility and accumulation. As a result of this realization, Card (2013) argues that the subject of social science research is more in need of organizing and analysis of current or already existing research than it is with carrying out new and further research. Following this, a substantial number of empirical research on the relationship between LM and firm performance have been conducted. As a result, this study intends to revisit previous related studies that have investigated the lean manufacturing and performance relationship. The goal for this is to properly examine them and identify any disparities, and then quantitatively merge these inconsistencies and contradictions in order to arrive at a more precise and generalized conclusion where other research works in a similar field fell short. Many others, for example (Abru-ledon et al., 2018; Gonçalves et al., 2019; Chao-chao Li, 2020), just like this research, have conducted meta-analytical studies to synthesize evidence about the association of key lean manufacturing constructs with the success of operational performance.

### 2.16 Summary

A detailed description of how the meta-analysis was conducted is presented in this chapter. This research is about a meta-analytical review of the ILMP- OP relationship for studies between the years 2010 and 2020. A meta-analytical evaluation has been argued to be one of the most effective techniques for correcting a number of artifacts such as measurement and sampling errors.

The chapter establishes a comprehensive approach on how the included studies were arrived at from 605 to the preliminary 50 and finally to the 30 that were used in the meta-analytical computations.

Pearson's correlation coefficient (r) was adopted as the uniform effect size for this review for those studies that used other methods to report their effect size. This was converted to r using the formulas described in the chapter.

Corrections for statistical artifacts (sampling error and measurement error to be precise) discovered in the studies were made to get rid of errors in their findings that might have resulted from their samples, sampling techniques, and statistical analysis of empirical data.

Because of the diverse nature of the studies, the random-effect model was adopted for the analysis over the fixed-effect model. And as a result, there was a higher chance of heterogeneity even after the correction of the statistical artifacts. Hence, efforts were made to assess the degree of the heterogeneity as well as ascertain how this could affect the ILM implementation on operational performance relationships.

Coming to the next chapter, the organization is done as follows; introduction and a detailed explanation of the findings and data analysis are done in the subsequent section. Following this section, the research methodology is discussed in further detail, and the meta-analysis results are presented. Finally, the conclusions on the research are presented, which include theoretical implications, managerial implications, limitations, and research question recommendations.

# CHAPTER 3: FINDINGS AND DATA ANALYSIS

## 3.1 Introduction

The findings of the study, as well as the data analysis and interpretation, are presented in this part. This is based on the data obtained from thirty studies conducted as part of a meta-analytical study of the impact of internal lean manufacturing methods on manufacturing enterprises' operational performance between 2010 and 2020. A summary of these studies and different results is presented with the details therein, as seen in the tables to follow. This is followed by the graphical representation of the basic and important information of each of the studies. This includes the journal names, year of publication of the studies, the geographical or economy type representation of the sample size of each study.

The results of the two key hypotheses are then reported, followed by the results of the moderator analyses, and the chapter finishes with an outlier and sensitivity analysis, as well as a review of the publishing bias.

Then the description of study characteristics follows every data presentation as well as all the necessary procedures and discussion leading to actual hypotheses testing. The results of the data analysis were imported into Microsoft Word for a presentation from the software application Jamovi, which was employed for meta-analytical computations in the current study because of its being an open-source, free-to-use software and able to produce reliable and accurate results

In the end, all the research questions are duly answered, and the objectives of the study are achieved in this chapter.

## 3.2 Profile of the studies

The table shows the outlook of thirty studies analyzed with their respective correlations ranging from (r=0.183 to r=0.897), which is the highest. It consists of the authors of the studies, the sample sizes, the journal names, the statistical method used, and the country of origin for each of the studies. The journals are represented with abbreviated initials, which are given in detail in the appendices. From table 5, N represents the sample size, r is the effect size picked from each study representing the correlation that exists in the ILMP-OP relationship.

**Table 5: Profile of the included papers**

| No. | Study | N | Journal | Statistical method | r | Country |
|---|---|---|---|---|---|---|
| 1 | Panwar et al. (2017) | 121 | JPP&C | Partial Least Squares | 0.844 | India |
| 2 | Khanchanapong et al. (2014) | 186 | IJPE | SEM/Bivariate correlation | 0.183 | Thailand |
| 3 | Rahman et al. (2010) | 187 | JMTM | Regression analysis | 0.572 | India |
| 4 | Valente et al. (2019) | 329 | JMTM | PLS-SEM | 0.640 | Portugal |
| 5 | Marodin et al. (2017) | 64 | JMTM | Regressıon | 0.441 | Brazil |
| 6 | Chavez et al. (2013) | 228 | IJOPM | Bivariate correlations | 0.253 | Ireland |
| 7 | Negrão et al. (2020) | 217 | PPC | PLS-SEM | 0.554 | Brazil |
| 8 | Onofrei et al. (2019) | 528 | IJOPM | Regression analysis | 0.475 | Europe, Asia, and North America |
| 9 | Al-Zu'bi et al. (2015) | 157 | EMR | Regression | 0.523 | Jordan |
| 10 | Nawanir et al. (2010) | 139 | JTOM | Regression & Bivariate correlation | 0.562 | Indonesia |
| 11 | Chi Phan et al. (2019) | 280 | MDPI | Regression | 0.376 | Europe, ME, Asia |
| 12 | Wickramasinghe and Perera (2016) | 30 | JMTM | Bivariate correlations | 0.640 | Sri Lanka |
| 13 | Chavez et al. (2015) | 228 | IJPE | Bivariate correlations | 0.349 | Ireland |
| 14 | Sahoo (2019) | 148 | IJQRM | Bivariate correlations | 0.668 | India |
| 15 | Sezen et al. (2011) | 207 | IJPR | Bivariate correlations | 0.501 | Turkey |
| 16 | Alsmadi et al. (2012) | 148 | TQMBE | Regression analysis | 0.802 | UK |
| 17 | Filho et al. (2016) | 64 | TQMBE | Regression & correl. | 0.386 | Brazil |
| 18 | Wickramasinghe & Wickramasinghe (2017) | 1189 | JMTM | Hierarchical regression analysis | 0.582 | Sri Lanka |
| 19 | Sahoo & Yadav (2017) | 121 | JMTM | Multiple regression | 0.490 | India |
| 20 | Costa et al (2020) | 145 | Food control | SEM | 0.678 | USA and Brazil |
| 21 | Saini & singh (2019) | 183 | IJLSS | Multiple regression | 0.862 | India |
| 22 | Nawanir et al. (2013) | 139 | JMTM | Multiple regression | 0.495 | İndonesia |
| 23 | Yadav et al. (2019) | 425 | IMDS | SEM | 0.897 | India |
| 24 | Zarinah et al. (2017) | 44 | JFAS | Regression analysis | 0.719 | Malaysia |
| 25 | Iranmanesh et al. (2019) | 187 | MDPI | PLS | 0.310 | Malaysia |
| 26 | Shafiq et al. 2019 | 210 | TQMBE | SEM | 0.505 | Pakistan |
| 27 | Kannan and Keah-Choon Tan (2015) | 556 | IJSCF | SEM | 0.085 | USA & Europe |
| 28 | Belekoukias et al. (2014) | 140 | IJPR | Linear regression | 0.538 | Multiple |
| 29 | Juan A. Marin-Garcia and Tomas Bonavia (2014) | 101 | IJPR | PLS-SEM | 0.344 | Spain |
| 30 | Shashi et al. (2019) | 374 | IJPE | SEM | 0.454 | India |

### 3.3 Publication years of sample studies

As can be seen from figure 7, 2019 was the year from which the highest number of studies (8) was drawn, followed by 2017 (6), 2014 (4), 2020 (2), 2010 (2), and the rest of the years have a distribution of one study each. The highest representation of the studies in the later years, i.e., 2019 and 2020, shows that this study is up-to-date with the latest developments in the world, such as the outbreak of the pandemic, technology evolutions, economy, automation, and the advancement of the information age. This is because current studies present the prevailing circumstances as opposed to the earlier studies which factored in those circumstances at those times. However, this uniform distribution again gives a balanced inclusion of the studies, which helps to involve a wide range of circumstances from one given period to the other and their possible effect on the study.

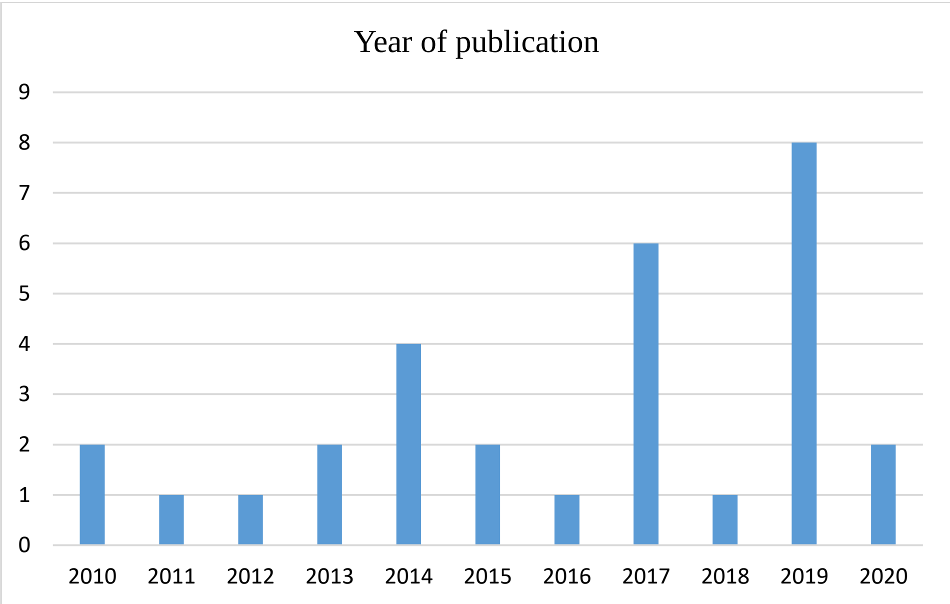


**Figure 7: The distribution of years for the studies used.**

### 3.4 Statistical methods used in the study

Table 6 shows a total of four statistical methods used and in other cases where one or more techniques were combined and used in one given study. The structural equation modeling (SEM) was the most applied method followed by studies that used both bivariate correlations with SEM (5x), then the different types of regression, i.e., hierarchical regression (3x), then partial least squares-SEM (2x), correlation and regression (2x) and then the rest of the methods which found application in each one of the studies.

The statistical methods utilized in this study are the most prominent statistical approaches used in most empirical studies in the domain of operations management.

**Table 6: Statistical methods used**

| Statistical Method | No. of papers |
|---|---|
| Multiple regression analysis | 2 |
| Bivariate correlations, SEM | 5 |
| Partial Least Squares -SEM | 2 |
| Ordinary Least Squares regression analysis | 1 |
| Ordinary Least Squares regression, correlation analysis | 1 |
| PLS-SEM, correlation analysis | 1 |
| Ordinary Least Squares model, correlation | 1 |
| Hierarchical regression analysis | 3 |
| Pearson correlation, multiple regression, PCA, and simple regression | 1 |
| Correlation and regression analysis | 2 |
| SEM, OLS regression | 1 |
| Structural Equation Modelling | 5 |
| Correlation, regression, canonical analysis, and ANOVA | 1 |
| Multiple regression and Correlation | 1 |
| Partial Least Squares | 2 |
| Linear regression analysis, Correlation analysis, SEM | 1 |

### 3.5 Geographical distribution of the sample

The geographical representation of the 7,075 manufacturing firms shows a large inclusion of firms from the Asia Pacific region (4,032) followed by Europe (1,385), the Middle East (390), South America (345), North America (82), and the multiple numbers of firms (845) spread across different continents. The high figures of firms in Asia pacific figures point to a realization of the emerging industrial economy in this region. The World Bank, the IMF, and OECD, and WTO have all pointed to the fast-growing manufacturing sector in these countries. With this has come the implementation of different techniques to achieve optimal and efficient shop floor operations, including internal lean manufacturing, to meet the needs and challenges rising rapidly in the various industrial sectors like firm performance improvement programs.

In figure 8 is a bar chart showing the geographical representation of the countries from which firms in the sample were selected.

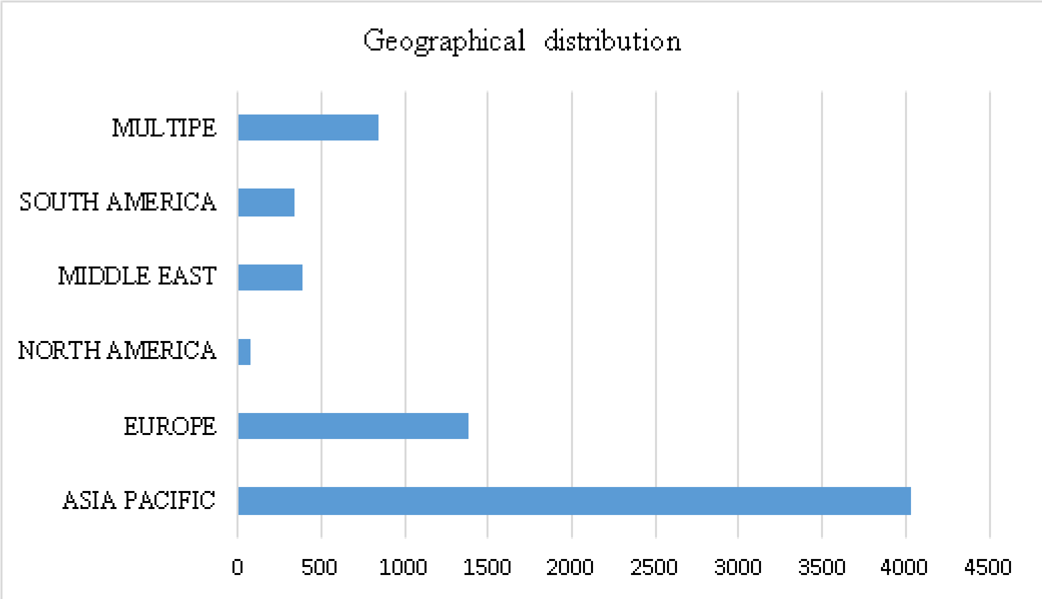


**Figure 8: Geographical representation of the countries**

### 3.6 Distribution of papers by journal

The latest version of the 2018 CABS quality journal guide lists and ranks some of the highest quality journals used in business, social, political, engineering and operations research. The Chartered Association of Business Schools (CABS) journal quality guide is a reliable tool for assessing and indicating the quality of journals in which the academics researching the business management field publish their papers, articles based on editorial policy, peer review, and expert judgments. It covers a wide range of journals in the business and management industry with high levels of internal and external reliability, dependability, and integrity (Rowlinson et al., 2011). CABS is a highly influential journal guide that helps management scholars to make decisions about where to have their work published in the operations and accounting field by ranking journals on a scale of 1 to 6* (Hsieh and Chang 2009)

As can be seen in Table 7, most of the journals used in this study are ranked mainly from 1st and 6th, being the lowest. This further affirms that this study is of high quality because it drew studies from a pool of highly ranked, worthwhile, and accepted journals.

Journals used like Journal of Manufacturing Technology Management, International Journal of Lean Six Sigma, and International Journal of Production Economics are ranked 1st in CABS Journal guide list as shown. The highly ranked journals were also the most frequently used in the research, e.g., The Journal of Manufacturing Technology Management (6x), Total Quality Management & Business Excellence (3x), International

Journal of Operations and Production Management (4x), International Journal of Operations and Production Management (3x), International Journal of Production Research (3x), among others.

**Table 7: Journal distribution for the included papers.**

| Journal Name | Ranking | No. of papers | % |
|---|---|---|---|
| Journal of Manufacturing Technology Management | 1 | 6 | 20 |
| International Journal of Production Economics | 3 | 4 | 13.33 |
| International Journal of operations & production management | 4 | 3 | 10 |
| International Journal of Production Research | 3 | 3 | 10 |
| Total Quality Management & Business Excellence | 2 | 3 | 10 |
| International Journal of Quality & Reliability Management | 2 | 2 | 6.67 |
| Engineering Management Research | N/A | 1 | 3.33 |
| Food Control | 4 | 1 | 3.33 |
| Industrial Management & Data Systems | 1 | 1 | 3.33 |
| International Journal of Lean Six Sigma | 1 | 1 | 3.33 |
| Journal of Fundamental and Applied Sciences | | 1 | 1 |
| Journal of Technology and Operations Management | N/A | 1 | 3.33 |
| MDPI Sustainability Journal | N/A | 1 | 3.33 |
| Production Planning and Control | 3 | 1 | 3.33 |
| Supply Chain Forum: An International Journal | 1 | 1 | 3.33 |

N/A- ranking not available in CABS journal

### 3.7 Determining the number of studies for inclusion in the meta-analysis

There are no definite number of studies that must be reached for conducting meta analysis though different researchers strive to have as many studies as possible to concretise the statistical power of their research or analysis (see Kirca et al. 2005).

The number of studies usually included in the analysis is based on a number of factors such as the number of studies done on a given subject, the time frame in which the studies were done, the nature of the effect size required  (see Lipsey and Wilson 2001) and other stated criteria depending on one researcher to another.

For instance, as seen in table 8, the lowest number of studies included in the meta-analysis was eight for Saridakis (2017), the medium is 25 studies for Liang et al. (2010), and the highest being 57 included studies for KangKang Yu et al. (2015).

The twenty-five reviewed meta-analysis studies looked at for the purpose of this research were mostly from the field of operations management and a handful from strategic and social management. In these 25 studies, it can be deduced that their mode is 21 included papers, the median is 26 papers, and the mean number of included papers is 30.

The average number of papers (30) found in the sampled meta-analyses according to our study was one of the reasons for choosing thirty as the number of studies to be included in this particular meta-analysis research study.

**Table 8: Meta-analytic reviews sampled and their number of included papers**

| No. | Meta-analysis study | No. of papers included |
|---|---|---|
| 1 | Balkundi and Harrison (2006) | 17 |
| 2 | Li and Cropanzano (2009) | 12 |
| 3 | KangKang Yu et al. (2015) | 57 |
| 4 | Sampaio et al., (2019) | 13 |
| 5 | Jitpaiboon and Subba (2007) | 50 |
| 6 | Kellermanns (2011) | 21 |
| 7 | Wowak et al., (2013) | 35 |
| 8 | Chen et al., (2021) | 32 |
| 9 | Miao et al., (2019) | 26 |
| 10 | Saridakis (2017) | 8 |
| 11 | Lim et al., (2002) | 15 |
| 12 | Sayla Sowat Siddiqui (2015) | 25 |
| 13 | Liang et al., (2010) | 42 |
| 14 | Cravo and Pizza (2019) | 36 |
| 15 | Eva Horváthová (2010) | 37 |
| 16 | Feng (2021) | 46 |
| 17 | Awe et al., (2018) | 24 |
| 18 | McEvoy and Cascio (1987) | 24 |
| 19 | Liu et al., (2018) | 21 |
| 20 | Ali Mohammad Mosadeghrad (2014) | 37 |
| 21 | Ahmad (2015) | 20 |
| 22 | Prashar (2017) | 12 |
| 23 | Rosenbusch et al., (2011) | 42 |
| 24 | Ataseven and Nair (2017) | 40 |

| | | |
|---|---|---|
| 25 | Sharma SO (2015) | 58 |
| | Average no. of studies | 30 |

### 3.8 Meta-analysis procedure

Following Hunter and Schmidt's (2004) meta-analysis procedure, this research set out to ascertain the impact of implementing internal lean manufacturing practices on the operational performance of manufacturing firms. This is because, according to Hunter and Schmidt (2004), meta-analysis is a quantitative method for analyzing effect sizes across a body of research.

Reviewing much of the literature in the many of these studies adopted and those dropped revealed a lot of contradiction and inconsistency from one result to the other. Because the most reliable way to generalize the empirical results of previous studies is by carrying out a meta-analysis review (Raudenbush et al., 1991), this research, therefore, embarked on taking up all these studies and extracting important data from them, and then aggregating this data from each of these studies to obtain a single generalized result of the ILMP-operational performance association.

The main analysis itself was carried out in three main stages based on the research questions and hypotheses. But prior to the test of hypotheses, a heterogeneity test was conducted for all the proposed relationships to assess the significance and the degree of variation in effect sizes that are attributable to systematic cross-sample variability. The most frequently used method of heterogeneity analysis being Cochran's Q-test together with the $I^2$ index (Higgins and Thompson, 2002), in which the existence of heterogeneity is determined by the Q-test and its degree determined by the $I^2$ index (Huedo-Medina et al., 2006). Each of the two statistical variables (Q and $I^2$ ) was thus calculated and recorded in this meta-research. The detailed description of the three stages, as well as the heuristics of analysis, is presented as follows;

### 3.9 Stage I: Aggregate ILM impact on operational performance

Here the effect of a combined total of the six internally related constructs under ILM on operational performance was found to be positive and significant.

Sampling error and measurement error were corrected for the final data used. In the studies, the larger the sample size, the larger the weight assigned in the computations where the compound attenuation factor for each study is multiplied by the study's sample size to arrive at the weight of the study. According to Hunter and Schmidt (1990), the recommended formula for computing the Attenuation factor (A) is getting the product of the square root of the Cronbach's alpha for each independent and dependent variable. And to calculate study weights, it's the product of the square of the attenuation factor and the size of the sample W = N x A ².

$A = \sqrt{\check{r}_{xx}} \cdot \sqrt{\check{r}_{yy}}$ , where A is the attenuation factor

The data is presented in the table below with the sample size, independent variable reliability, dependent variable reliability, the correlation of the studies, and their corrected correlations.

As can be seen from table 9, the biggest sample size is 1,189 firms, and the smallest one is (thirty) 30 firms.

**Table 9: Empirical data retrieved from the papers used in the research**

| **Study** | **N** | **LP reliability** | **OP reliability** | **r(LP-OP)** | **ř** |
|---|---|---|---|---|---|
| Panwar et al. (2017) | 121 | 0.771 | 0.750 | 0.844 | 0.999 |
| Khanchanapong et al. (2014) | 186 | 0.840 | 0.800 | 0.183 | 0.223 |
| Rahman et al. (2010) | 187 | 0.794 | 0.759 | 0.572 | 0.737 |
| Valente et al. (2019) | 329 | 0.888 | 0.798 | 0.640 | 0.760 |
| Marodin et al. (2017) | 64 | 0.826 | 0.783 | 0.441 | 0.548 |
| Chavez et al. (2013) | 228 | 0.721 | 0.761 | 0.253 | 0.342 |
| Negrão et al. (2019) | 217 | 0.894 | 0.904 | 0.554 | 0.616 |
| Onofrei et al. (2019) | 528 | 0.900 | 0.868 | 0.475 | 0.537 |
| Al-Zu'bi et al. (2015) | 157 | 0.707 | 0.709 | 0.523 | 0.739 |
| Nawanir et al. (2010) | 139 | 0.866 | 0.783 | 0.562 | 0.682 |
| Chi Phan et al. (2019) | 280 | 0.826 | 0.850 | 0.376 | 0.449 |
| Wickramasinghe et al. (2016) | 30 | 0.755 | 0.765 | 0.640 | 0.842 |
| Chavez et al. (2015) | 228 | 0.721 | 0.801 | 0.349 | 0.459 |
| Sahoo (2019) | 148 | 0.888 | 0.8656 | 0.668 | 0.762 |
| Sezen et al. (2011) | 207 | 0.920 | 0.820 | 0.501 | 0.577 |
| Alsmadi et al. (2012) | 148 | 0.822 | 0.908 | 0.802 | 0.928 |
| Filho et al. (2016) | 64 | 0.711 | 0.783 | 0.386 | 0.517 |
| G.L.D. Wickramasinghe & V. Wickramasinghe (2017) | 1189 | 0.860 | 0.900 | 0.582 | 0.662 |
| Sahoo & Yadav (2017) | 121 | 0.731 | 0.725 | 0.490 | 0.673 |

| | | | | | |
|---|---|---|---|---|---|
| Costa et al. (2020) | 145 | 0.860 | 0.900 | 0.678 | 0.771 |
| Saini & singh (2019) | 183 | 0.972 | 0.953 | 0.862 | 0.896 |
| Nawanir et al. (2013) | 139 | 0.690 | 0.608 | 0.495 | 0.764 |
| Yadav et al. (2019) | 425 | 0.835 | 0.775 | 0.897 | 1.115 |
| Zarinah et al. (2017) | 44 | 0.944 | 0.938 | 0.719 | 0.764 |
| Iranmanesh et al. (2019) | 187 | 0.826 | 0.884 | 0.31 | 0.363 |
| Shafiq et al. (2017) | 210 | 0.859 | 0.848 | 0.505 | 0.592 |
| Vijay R. Kannan and Keah-Choon Tan (2015) | 556 | 0.866 | 0.719 | 0.085 | 0.108 |
| Belekoukias et al. (2014) | 140 | 0.826 | 0.783 | 0.538 | 0.669 |
| Juan A. Marin-Garcia and Tomas Bonavia (2014) | 101 | 0.826 | 0.783 | 0.344 | 0.428 |
| Shashi et al. (2019) | 374 | 0.826 | 0.783 | 0.454 | 0.565 |

N- Sample size, LM- Lean manufacturing, r- correlations, ř- corrected correlations

### 3.9.1 Data stage II: Individual internal lean manufacturing practices and operational performance

At this stage, we look at each of the six practices of ILM individually and how each affects operational performance when implemented. As can be seen, each of the six ILM practices has been almost uniformly represented with quite a good number of studies under each one of them (over 10), with the exception of continuous flow production (6 studies). These practices, including setup time reduction, total productive maintenance, statistical process control, pull production, and employee involvement, were investigated for any positive or significant impact on operational performance. The weight of each study weight (W) was calculated and is shown.

**Table 10: Data from the papers under each individual Internal lean practice**

| Study | N | LP reliability | OP reliability | r(LP-OP) | ř | Study W |
|---|---|---|---|---|---|---|
| **Set up time reduction** | | | | | | |
| Panwar et al. 2017 | 121 | 0.802 | 0.750 | 0.220 | 0.284 | 72.782 |
| Rahman et al. 2010 | 187 | 0.863 | 0.759 | 0.427 | 0.528 | 122.488 |
| Marodin et al. 2017 | 64 | 0.736 | 0.797 | 0.152 | 0.198 | 37.542 |
| Negrão et al. 2019 | 217 | 0.865 | 0.904 | 0.154 | 0.174 | 169.685 |
| Al-Zu’bi et al. 2015 | 157 | 0.726 | 0.709 | 0.196 | 0.273 | 80.813 |
| Nawanır et al 2010 | 139 | 0.837 | 0.783 | 0.400 | 0.494 | 91.097 |
| Chi Phan et al. 2019 | 280 | 0.700 | 0.797 | 0.180 | 0.241 | 156.212 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Chavez et al. 2015 | 228 | 0.721 | 0.801 | 0.349 | 0.459 | 131.675 |
| Sahoo 2019 | 148 | 0.893 | 0.797 | 0.676 | 0.801 | 105.335 |
| Sezen et al. 2011 | 207 | 0.605 | 0.797 | 0.199 | 0.287 | 99.812 |
| Alsmadi  et al. 2012 | 148 | 0.797 | 0.797 | 0.863 | 1.083 | 94.011 |
| Filho et al. 2016 | 64 | 0.736 | 0.797 | 0.099 | 0.129 | 37.542 |
| Costa et al. 2020 | 145 | 0.810 | 0.900 | 0.781 | 0.915 | 105.705 |
| Saini & singh 2019 | 183 | 0.963 | 0.953 | 0.747 | 0.780 | 167.946 |
| Nawanir et al. 2013 | 139 | 0.600 | 0.608 | 0.295 | 0.488 | 50.707 |
| Iranmanesh et al. 2019 | 187 | 0.874 | 0.884 | 0.235 | 0.267 | 144.479 |
| Vijay R. Kannan and Keah-Choon Tan 2015 | 556 | 0.865 | 0.719 | -0.170 | -0.216 | 345.796 |
| **Total Productive Maintenance** | | | | | | |
| Panwar et al. 2017 | 121 | 0.773 | 0.750 | 0.752 | 0.988 | 70.150 |
| Valente et al. 2019 | 329 | 0.854 | 0.927 | 0.779 | 0.876 | 260.455 |
| Negrão et al. 2019 | 217 | 0.875 | 0.904 | 0.149 | 0.168 | 171.647 |
| Nawanir et al 2010 | 139 | 0.831 | 0.783 | 0.482 | 0.598 | 90.444 |
| Wickramasinghe et al 2016 | 30 | 0.755 | 0.765 | 0.640 | 0.842 | 17.327 |
| Sahoo 2019 | 148 | 0.892 | 0.866 | 0.679 | 0.773 | 114.326 |
| Sezen et al. 2011 | 207 | 0.678 | 0.820 | 0.048 | 0.064 | 115.084 |
| Alsmadi  et al. 2012 | 148 | 0.826 | 0.908 | 0.898 | 1.037 | 111.001 |
| Marodin et al. 2017 | 64 | 0.661 | 0.835 | 0.121 | 0.163 | 35.324 |
| Costa et al. 2020 | 145 | 0.890 | 0.900 | 0.811 | 0.906 | 116.145 |
| Saini & singh 2019 | 183 | 0.976 | 0.953 | 0.807 | 0.837 | 170.213 |
| Nawanir et al. 2013 | 139 | 0.700 | 0.608 | 0.428 | 0.656 | 59.158 |
| Belekoukias et al. 2014 | 140 | 0.809 | 0.835 | 0.311 | 0.378 | 94.572 |
| **Statistical Process Control** | | | | | | |
| Panwar et al. 2017 | 121 | 0.779 | 0.750 | 0.261 | 0.341 | 70.694 |
| Valente et al. 2019 | 329 | 0.880 | 0.798 | 0.852 | 1.017 | 231.037 |
| Negrão et al. 2019 | 217 | 0.890 | 0.904 | 0.177 | 0.197 | 174.59 |
| Nawanır et al. 2010 | 139 | 0.870 | 0.783 | 0.436 | 0.528 | 94.688 |
| Chi Phan et al. 2019 | 280 | 0.910 | 0.850 | 0.275 | 0.313 | 216.58 |
| Sahoo 2019 | 148 | 0.882 | 0.866 | 0.640 | 0.732 | 113.044 |
| Sezen et al. 2011 | 207 | 0.740 | 0.820 | 0.300 | 0.385 | 125.608 |
| Alsmadi  et al. 2012 | 148 | 0.852 | 0.908 | 0.856 | 0.973 | 114.495 |
| Sahoo & Yadav 2017 | 121 | 0.739 | 0.725 | 0.514 | 0.702 | 64.829 |
| Costa et al. 2020 | 145 | 0.870 | 0.900 | 0.845 | 0.955 | 113.535 |
| Saini & singh 2019 | 183 | 0.977 | 0.953 | 0.801 | 0.83 | 170.388 |
| Shafiq et al. 2017 | 210 | 0.854 | 0.848 | 0.427 | 0.502 | 152.08 |
| Vijay R. Kannan and Keah-Choon Tan 2015 | 556 | 0.867 | 0.719 | 0.340 | 0.431 | 346.595 |
| Belekoukias et al. 2014 | 140 | 0.855 | 0.833 | 0.175 | 0.207 | 99.71 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **Pull Production** | | | | | | |
| Rahman et al. 2010 | 187 | 0.863 | 0.759 | 0.427 | 0.528 | 122.488 |
| Marodin et al. 2017 | 64 | 0.736 | 0.809 | 0.152 | 0.197 | 38.107 |
| Chavez et al. 2013 | 228 | 0.721 | 0.761 | 0.253 | 0.342 | 125.099 |
| Negrão et al. 2019 | 217 | 0.937 | 0.904 | 0.071 | 0.077 | 183.809 |
| Al-Zu’bi et al. 2015 | 157 | 0.687 | 0.709 | 0.316 | 0.453 | 76.472 |
| Nawanır et al. 2010 | 139 | 0.926 | 0.783 | 0.421 | 0.494 | 100.783 |
| Chavez et al. 2015 | 228 | 0.721 | 0.801 | 0.349 | 0.459 | 131.675 |
| Sahoo 2019 | 148 | 0.893 | 0.866 | 0.676 | 0.769 | 114.454 |
| Sezen et al. 2011 | 207 | 0.609 | 0.820 | 0.218 | 0.308 | 103.372 |
| Alsmadi et al 2012 | 148 | 0.830 | 0.908 | 0.801 | 0.923 | 111.539 |
| Filho et al. 2016 | 64 | 0.736 | 0.809 | 0.099 | 0.128 | 38.107 |
| GLD Wickramasinghe and Vathsala Wickramasinghe 2017 | 1189 | 0.840 | 0.900 | 0.343 | 0.394 | 898.884 |
| Costa et al. 2020 | 145 | 0.850 | 0.900 | 0.702 | 0.803 | 110.925 |
| Nawanir et al. 2010 | 139 | 0.890 | 0.608 | 0.395 | 0.537 | 75.216 |
| Iranmanesh et al. 2019 | 187 | 0.859 | 0.884 | 0.114 | 0.131 | 142 |
| Vijay R. Kannan and Keah-Choon Tan 2015 | 556 | 0.865 | 0.719 | -0.170 | -0.216 | 345.796 |
| Belekoukias et al. 2014 | 140 | 0.772 | 0.809 | 0.421 | 0.533 | 87.437 |
| **Employee Involvement** | | | | | | |
| Marodin et al. 2017 | 64 | 0.736 | 0.863 | 0.085 | 0.107 | 40.6508 |
| Negrão et al. 2019 | 217 | 0.956 | 0.904 | 0.165 | 0.177 | 187.537 |
| Sahoo 2019 | 148 | 0.885 | 0.866 | 0.678 | 0.774 | 113.429 |
| Sezen et al. 2011 | 207 | 0.616 | 0.82 | 0.142 | 0.2 | 104.56 |
| Alsmadi et al 2012 | 148 | 0.814 | 0.908 | 0.799 | 0.929 | 109.389 |
| Filho et al. 2016 | 64 | 0.726 | 0.863 | 0.084 | 0.105 | 40.6504 |
| G.L.D. Wickramasinghe & V. Wickramasinghe 2017 | 1189 | 0.880 | 0.9 | 0.395 | 0.444 | 941.688 |
| Sahoo & Yadav 2017 | 121 | 0.722 | 0.725 | 0.465 | 0.643 | 63.3375 |
| Costa et al 2020 | 145 | 0.890 | 0.900 | 0.825 | 0.922 | 116.145 |
| Saini & singh 2019 | 183 | 0.970 | 0.863 | 0.793 | 0.867 | 153.191 |
| Iranmanesh et al. 2019 | 187 | 0.888 | 0.884 | 0.072 | 0.081 | 146.794 |
| Shafiq et al. 2017 | 210 | 0.868 | 0.863 | 0.150 | 0.173 | 157.308 |
| Vijay R. Kannan and Keah-Choon Tan 2015 | 556 | 0.867 | 0.863 | 0.340 | 0.393 | 416.011 |
| Juan A. Marin-Garciaa and Tomas Bonavia (2014) | 101 | 0.833 | 0.863 | 0.281 | 0.331 | 72.6068 |
| **Continuous flow production** | | | | | | |
| Valente et al. 2019 | 329 | 0.805 | 0.798 | 0.699 | 0.872 | 211.346 |
| Negrão et al. 2019 | 217 | 0.846 | 0.904 | 0.178 | 0.204 | 165.958 |
| sahoo 2019 | 148 | 0.893 | 0.866 | 0.676 | 0.769 | 114.454 |
| Alsmadi et al. 2012 | 148 | 0.815 | 0.908 | 0.788 | 0.916 | 109.523 |
| Costa et al.2020 | 145 | 0.830 | 0.900 | 0.689 | 0.797 | 108.315 |
| Shafiq et al. 2017 | 210 | 0.854 | 0.848 | 0.427 | 0.502 | 152.08 |

#### 3.9.1.1 Forest plot illustration

Figure 9 below illustrates the included studies on a forest plot diagram. The forest numerically and graphically demonstrates the summary effect size and the corresponding 95% credibility interval (CI). According to (Borenstein et al. 2019), apart from highlighting any anomalies with the data set, forest plots are also very important for the visual explanation, demonstration, and assessment of meta-analysis results.

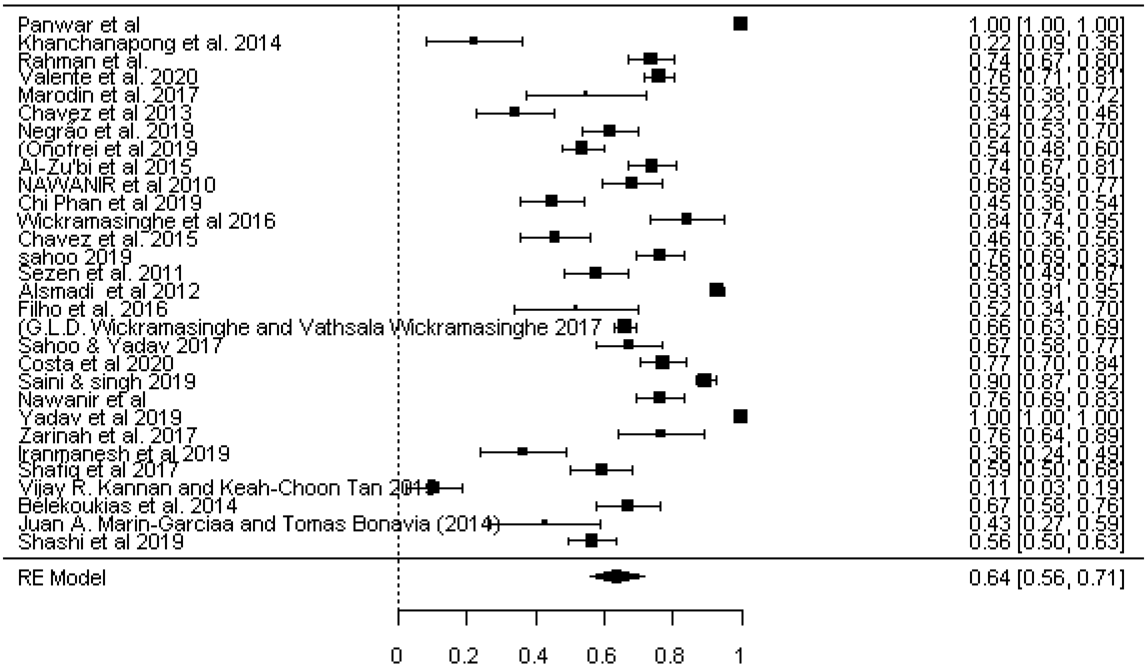


**Figure 9: Forest plot for each of the 30 studies**

In the figure above, the centerline is at zero coordinate, and the positive values are on the right and negative values on the left side of the centerline. The distance between the boxes and the center line indicates the magnitude of the effect size on each side. However, it is noted that nearly all the adjusted effect size values are to the right of the centerline ranging between ($0.11< r < 1.00$), and the 95% credibility interval varies from a low of 0.03 (i.e., Kannan and Tan, 2015) to the highest of 0.99 (i.e., Panwar et al. 2017). The positive effect sizes (to the right) indicate a positive relationship between ILMP and OP.

The forest plot at the bottom in a diamond shape depicts the summary effect size and its CI95%. The center of the diamond at 0.643 is the final summary effect size, and the width of the diamond represents the CI95% interval between ($0.56\leq r \leq 0.71$) lying at the extremes.

### 3.9.2 Stage III: Moderator analysis

To ascertain the presence of variations from one factor to another in the two major hypotheses, a test of heterogeneity was done. This showed the magnitude of variation in the two major hypotheses based on the three moderating factors firm size, firm type, and the type of economy in which the sample size of manufacturing firms operates.

Publication bias was another factor looked into at this stage to find out if any sufficient number of published or unpublished studies to alter the general effect size was left out. Therefore, two methods, that is to say, the funnel plot and the Classic fail-safe N, were adopted to perform the analysis.

There are several other techniques to perform such publication bias analysis, but the fail-safe N was selected because of its simplicity and it is being able to be performed by the meta-analysis software used.

This is calculated as,

$$N_{fs} = k\left[\frac{Z_s}{Z_\alpha}\right]^2 - K$$

Where k is the number of studies in the meta-analysis, $Z_s$ is Stouffer's sum, and $Z_\alpha$ is the one-tailed Z score associated with the required α.

### 3.9.3 Heuristics for hypothesis testing

Using Hunter and Schmidt's (2004) meta-analysis procedure, the Jamovi software was applied to carry out the meta-analysis computations. However, the heuristics for hypothesis testing was based on Cohen's (1992) guidelines and the significance level (p-value). According to Cohen (1992), an effect size (r) of 0.1 indicates a small effect of 0.3, representing medium effect, and 0.5 and above indicates large effects. While Cohen's (1992) guidelines define the strength of the relationship (effects), a p-value less than or equal to 0.05 will help determine the statistical significance of the relationship.

While looking at heterogeneity, the non-uniformity in the results of each study was measured by the combination of Cochran's Q and the $I^2$ statistics. Q as the chi-square estimate is expressed as the weighted sum of squared differences between individual study effects and the aggregated value of the effect across studies, with the weights being those used in the pooling approach. Q is calculated as a chi-square statistic with k (the number of studies) and 1 degree of freedom deducted. When the number of studies is minimal, Q weilds low power as a complete test of heterogeneity (Gavaghan et al., 2000). In contrast, if the number of studies (k) is very great, Q weilds a lot of power as a test of heterogeneity, according to (Higgins et al., 2003). The $I^2$ statistic denotes the proportion of variation between studies that is due to heterogeneity rather than chance (Higgins et al., 2003; Higgins and Thompson, 2002).

$I^2$ = 100 percent x (Q-df)/Q, for example.

$I^2$ is a natural and basic expression of the irregularity of the results from studies. An $I^2$ statistics value of 25% is generally considered as low heterogeneity, 50% as moderate and <75% as high heterogeneity. The test of heterogeneity in this study was therefore guided by this rule.

### 3.10 Results of the meta-analysis

Based on the above explanation, the analysis done and the results obtained are presented in table form as shown. The results generated from the Word, Excel spreadsheets, and the software as a result of feeding in the quantitative and qualitative data retrieved from the thirty are presented in this section and its sub-sections

#### 3.10.1 Heterogeneity test

The results of this test are presented in table 11. Because all the relationships have $I^2$ above 75%, this shows heterogeneity is higher in this test. The Q tests for all the relationships are significantly further affirming a present and significant heterogeneity in each of the associations from the 30 studies.

**Table 11: Results from the heterogeneity analysis**

| **Association** | **Q** | **df** | **P** | **SE** | **$I^2$** |
|---|---|---|---|---|---|
| H1: ILMP→OP | 2760.684 | 29 | < .001 | 0.0121 | 99.99% |
| H2a: Employee involvement → OP | 1052.209 | 13 | < .001 | 0.0418 | 99.26% |
| H2b: Flow production → OP | 179.102 | 5 | < .001 | 0.0454 | 99.23% |
| H2c: Pull production → OP | 1346.433 | 16 | < .001 | 0.0302 | 98.10% |
| H2d: Set up time reduction → OP | 2181.076 | 16 | < .001 | 0.0366 | 99.27% |
| H2e: Statistical Process control → OP | 1215.981 | 13 | < .001 | 0.032 | 99.89% |
| H2f: Total Prod. Maintenance → OP | 814.928 | 12 | < .001 | 0.0437 | 99.97% |

Note: df = degree of freedom; SE = variance; H = Hypothesis

### 3.10.2 Comparison between results obtained by formula and the software.

In this section, Hunter and Schidmt's formulae for calculating variables related to the summary effect size were fed into the Excel spreadsheet. As seen, nine variables were required to obtain the final result. Four of the basic results for each of the four basic variables were extracted directly from the thirty studies, and they formed the basis for the computation of the rest of the five variables. The correlation between aggregate ILMP-OP and then for each of the six ILMPs and OP is shown in table 15.

**Table 12: Calculation formulae the summary effect size in the excel spreadsheet**

| Sample size (N) | LP reliability (LPr) | OP reliability (Opr) | LP-OP correlation (r) | Attenuation factor (A) | Corrected correlation (ŕ) | Study Weight (W) | Study weight corrected correlation (ŕ*w') | Population correlation/summary effect size r" |
|---|---|---|---|---|---|---|---|---|
| | | | | $= \sqrt{LPr} * \sqrt{OPr}$ | $= r/A$<br>$= \frac{r}{(\sqrt{LPr} * \sqrt{Opr})}$ | $= N \times A^2$ | $= ŕ*w$<br>$= \left[\frac{r}{(\sqrt{LPr} * \sqrt{Opr})}\right] * N \times A^2$ | $= \frac{\sum ŕ*w'}{\sum w}$ |

Calculations were done using both the formulae of Hunter and Schmidt (2004) and the software. As seen in Table 12, data for LP reliabilities (LPr), OP reliabilities (OPr), sample sizes (N), and LP-OP effect sizes (r) were obtained directly from the thirty empirical studies. This then enabled calculating the attenuation factor (A), corrected correlation (ŕ), study weights (w), study weight corrected correlation ((ŕ*w'), and then finally the population correlation or the summary effect size (r”) of the research. From table 5, there was a very minimal acceptable discrepancy in the results obtained using the formula and those returned by the Jamovi software in the difference range of ($0.007< r <0.022$). All the results obtained using the two different methods are within the 95% credibility interval as shown, and therefore any one of them can be considered. For this research, though, results from the software were adopted as it was able to do computations for a very wide range of analyses, including heterogeneity analysis, moderation analysis, and the 95% CI, which were hard to compute manually by formulae.

**Table 13: Summary correlations computed by formula Vs software**

| Associations | Results by software | Results computed by formula | Difference | 95% CI (Lower, upper) | Remarks |
|---|---|---|---|---|---|
| **ILMP→OP** | 0.637 | 0.626 | 0.011 | 0.560, 0.714 | Both fall within the 95%CI |
| **EI →OP** | 0.449 | 0.442 | 0.007 | 0.278, 0.620 | Both fall within the 95%CI |
| **FP → OP** | 0.682 | 0.66 | 0.022 | 0.467, 0.896 | Both fall within the 95%CI |
| **PP → OP** | 0.409 | 0.398 | 0.008 | 0.270, 0.548 | Both fall within the 95%CI |
| **STP → OP** | 0.424 | 0.408 | 0.016 | 0.271, 0.577 | Both fall within the 95%CI |
| **SPC → OP** | 0.584 | 0.573 | 0.011 | 0.435, 0.734 | Both fall within the 95%CI |
| **TPM → OP** | 0.643 | 0.655 | 0.012 | 0.465, 0.821 | Both fall within the 95%CI |

### 3.10.3 Aggregate ILMP and Operational performance

From the table of results 14 based on Cohen's (1998) benchmarks, as per the results returned by the software, it can be reported from the analysis of the thirty studies comprising a sample of 7,075 firms that the ILMP- operational performance relationship (H1) is positively strong and significant, i.e. ( r= 0.637, P<0.001). Studies investigating a closely related relationship such as this one came to a closely similar conclusion, that is to say (Costa t al., 2020; Iranmanesh et al., 2019; Marodin et al., 2019) and others

The fail-safe N for ILMP-OP is 87,256.03, and it is greater than the critical number of studies, kc, which is 160. Whenever the failsafe is larger than the kc, this represents the absence of the file drawer problem (e.g., see Clark-Carter 1997; Rosenthal 1991). The 95% credibility interval is seen to range between 0.560 and 0.714, both large correlations according to Cohen (1992)'s standards. This implies that the result does not widely vary from one end of the limit to the other.

Regarding publication bias, since Failsafe N is greater than Kc for all the relationships, as seen in table 14, this signals the absence of the file-drawer problem in each of the relationships.

(See detailed explanation in section 3.10.7)

### 3.10.4 Individual ILM practices and operational performance

Measuring the impact of each ILM practice on OP (H2), the results point to all positive and significant relationships as presented in table 16. The 95% credibility interval for each of the associations is also observed to be within a relatively limited range of variation. The range of variation was seen to be only between positive correlations with just a difference in magnitude, i.e., small, medium, and large. There is no wide variation observed from one extreme end of the limit to the other, i.e., from a negative to a positive correlation.

#### 3.10.4.1 Employee involvement and operational performance

From the fourteen studies with a sample size of 3,540 that analyzed this relationship (H2a), a medium positive and significant association positive was discovered, i.e., ($r=0.449$, $P<0.001$). Such a result is backed by a similar conclusion reached by studies like (Iranmanesh et al. 2019; Kannan and Tan 2002; Marin-Garcia and Bonavia 2015; Sahoo and Yadav 2017; Saini and Singh 2020) that investigated a closely similar relationship. The 95% credibility interval is seen to range between 0.278 and 0.628, i.e., from small to large correlations according to Cohen (1992)'s standards. This implies that the result falls within limits with a relatively narrow variation.

The fail-safe N of 1,889.62 is larger than the critical number of studies which is 80 and therefore represents an absence of any publication bias.

#### 3.10.4.2 Continuous flow production and operational performance

This had the least number (six) of studies analyzing this relationship (H2b). With a sample size of 1,197 firms, however, it shows a strong positive correlation ($r=0.682$) and a significant association ($p<.001$) in agreement with a number of previously done studies that investigated a similar relationship and came up with a closely identical result. Such studies include but are not limited to (Costa et al. 2020; Negrão et al., 2020; Sahoo 2019; Shafiq et al., 2019). The 95% credibility interval is seen to range between 0.467 and 0.896, i.e., from medium to large correlations according to Cohen (1992)'s standards. This implies that the result varied narrowly within the lower and upper limits.

The correlation achieved under this relationship is one of the highest achieved in all the six ILM practices and therefore underscoring the importance of implementation of continuous flow production to impact the operational performance of manufacturing firms. In order to achieve higher operational performance yields, the focus should be on applying more of the continuous flow production.

The fail-safe N of 510.36 is larger than the kc (50), representing absence of any publication bias. The Fail safe number is observed to be the smallest obtained, and this was as a result of the fewest studies that were used to analyze this relationship.

#### 3.10.4.3 Pull production and operational performance

With seventeen different studies comprising a sample size of 4,143 firms analyzing this relationship (H2c), a positive medium and significant relationship is confirmed (r= 0.409, P<0.001). Previous studies which analyzed a related relationship came to a similar conclusion as the one in this study, such as (Al-Zu'bi 2015; Negrão et al. 2020; Roberto et al. 2013; Sahoo 2019). The 95% credibility interval is seen to range between 0.270 and 0.548, i.e., from small to large correlations according to Cohen (1992)'s standards. This shows that the result did not vary a lot from one extreme end of the limit to the other.

The fail-safe N of 3,551.01 is bigger than the critical number of studies (95), representing the absence of any publication bias in the study.

#### 3.10.4.4 Setup time reduction and operational performance

A total of seventeen studies representing 3,170 manufacturing firms analyzed this relationship (H2d) and found a positively medium and significant relationship (r=0.424, p<.001). A good number of studies investigating a closely related association corroborated this outcome (e.g., see Panwar et al. 2017; Phan et al., 2019; Rahman et al. 2010). The 95% credibility interval is seen to range between 0.271 and 0.577, i.e., from small to large correlations according to Cohen (1992)'s standards. This shows that the lower and upper limits for the result are relatively narrow.

With a fail-safe N 3,131.98 greater than $K_c$ of 95, the relationship has no presence of publication bias.

#### 3.10.4.5 Statistical process control and operational performance

Fourteen studies comprising a sample of 2,944 firms analyzed this relationship (H2e) and established a positively strong and significant result (r= 0.584, P<0.001). Other studies analyzing a closely similar relationship found a similarly identical outcome to this, such as (Belekoukias et al. 2014; Kannan and Tan 2015; Sahoo and Yadav 2007), and many others. The correlation here is stronger, signalling the need to prioritize the implementation of SPC over other practices if higher OP is to be achieved.

The 95% credibility interval is seen to range between 0.435 and 0.734, i.e., from medium to large correlations according to Cohen (1992)'s standards. This shows that the result was within a relatively narrow range of variation.

The fail-safe N (4,224.88) here is seen to be larger than the critical number of studies (80) and hence ruling out the presence of the file drawer problem.

### 3.10.4.6 Total productive maintenance and operational performance

Thirteen studies with a combined sample size of 2,010 firms analyzed this relationship (H2f) and found out a positively strong and significant outcome (r= 0.643, P<0.001). Previous studies analysing a closely related association corroborated the result achieved in this particular research, for instance, (Alsmadi, Lehaney, and Khan 2012; Costa et al. 2020; Marodin et al. 2019; Sahoo 2019; Saini and Singh 2020; Sezen et al. 2012; Wickramasinghe and Perera 2016).

The stronger correlation observed here, only second to that obtained in the continuous flow production-operational performance relationship signals the need for prioritization of TPM over other practices if higher operational performance is to be achieved.

The 95% credibility interval is seen to range between 0.465 and 0.821, i.e., from medium to large correlations according to Cohen (1992)'s standards. This shows that the result was within a relatively narrow range of variation.

The fail safe N of 3,126.43 is greater than the critical number of studies, kc of 75. This represents the absence of the file drawer problem in the TPM-OP relationship.

**Table 14: Results from the analysis of ILMP-OP association.**

| **Relationship** | **k** | **N** | **ŕ** | **P-value** | **95%CI (L, U)** | **SE** | **Z-value** | **failsafe N** | **kc** |
|---|---|---|---|---|---|---|---|---|---|
| H1: ILMP→FP | 30 | 7,075 | 0.637 | < .001 | 0.560, 0.714 | 0.0392 | 16.2 | 87,256.03 | 160 |
| H2a: EI.→ OP | 14 | 3,540 | 0.449 | < .001 | 0.278, 0.620 | 0.0873 | 5.14 | 1,889.62 | 80 |
| H2b: FP → OP | 6 | 1,197 | 0.682 | < .001 | 0.467, 0.896 | 0.109 | 6.23 | 510.36 | 40 |
| H2c: PP→ OP | 17 | 4,143 | 0.409 | < .001 | 0.270, 0.548 | 0.0709 | 5.78 | 3,551.01 | 95 |
| H2d: STP. → OP | 17 | 3,170 | 0.424 | < .001 | 0.271, 0.577 | 0.078 | 5.43 | 3,131.98 | 95 |
| H2e: SPC → OP | 14 | 2,944 | 0.584 | < .001 | 0.435, 0.734 | 0.0764 | 7.65 | 4,224.88 | 80 |
| H2f: TPM → OP | 13 | 2,010 | 0.643 | < .001 | 0.465, 0.821 | 0.0907 | 7.09 | 3,126.43 | 75 |

k-no. of studies, N-sample size, r- effect size, SE- standard error, kc- critical number of studies.

As seen from this table, prioritization of ILM practices should be in the order of continuous flow production, then total productive maintenance, statistical process control, employee involvement, setup time reduction and lastly pull production.

However, implementing them complementarily increases the overall operational performance, as shown by the correlation of the aggregate ILMP-OP association (r= 0.637).

### 3.10.5 Moderator analysis

The moderator analysis was carried to ascertain how each of the major relationships under scrutiny behaves if tried in different scenarios. These scenarios that were tested on the associations included firm size, industry type and type of economy in which the firms were operating. And these moderating factors were further divided into subgroups which were then tested on the different hypotheses under investigation. That is to say, under firm size, there are small, medium and large enterprises. Under industry type, there are process industries and discrete manufacturing industries. With this type of economy lies the emerging market economies and the advanced economies.

The findings of the moderator analysis revealed that each of the moderating factors and their subgroups has a significant (positive) impact on each of the established hypotheses.

From table 15 is a summary of the moderator variables for each of the 30 studies in the meta-analysis evaluation.

**Table 15: Moderator variables applied to the ILMP-OP relationship**

| No. | Study | Industry size | Industry Type | Type of Economy |
|---|---|---|---|---|
| 1 | Panwar et al. 2017 | SME, LE | Process | EME |
| 2 | Khanchanapong et al. 2014 | SME, LE | Discreet | EME |
| 3 | Rahman et al. 2010 | LE, SME | Process | EME |
| 4 | Valente et al. 2020 | SME | Process & Discrete | Advanced |
| 5 | Marodin et al. 2017 | SME, LE | Discrete | EME |
| 6 | Chavez et al. 2013 | SME, LE | Process & Discrete | Advanced |
| 7 | Negrão et al. 2019 | SME, LE | Process | EME |
| 8 | Onofrei et al. 2019 | SME, LE | Discrete | Advanced |
| 9 | Al-Zu’bi et al. 2015 | SME, LE | Process & Discrete | EME |
| 10 | Nawanır et al. 2010 | LE | Discrete | EME |
| 11 | Chi Phan et al. 2019 | ME, LE | Discrete | Advanced |
| 12 | Wickramasinghe et al. 2016 | N/A | Process | EME |
| 13 | Chavez et al. 2015 | SME, LE | Process & Discrete | Advanced |

| | | | | |
|---|---|---|---|---|
| 14 | Sahoo 2019 | LE | Process & Discrete | EME |
| 15 | Sezen et al. 2011 | SME, LE | Discrete | EME |
| 16 | Alsmadi et al. 2012 | SME, LE | Process & Discrete | Advanced |
| 17 | Filho et al. 2016 | SME, LE | Discrete | EME |
| 18 | G.L.D. Wickramasinghe & V. Wickramasinghe 2017 | N/A | Process | EME |
| 19 | Sahoo & Yadav 2017 | SME, LE | Process & Discrete | EME |
| 20 | Costa et al. 2020 | SME, LE | Process | A &EME |
| 21 | Saini & singh 2019 | SME, LE | N/A | EME |
| 22 | Nawanir et al. 2013 | LE | Process & Discrete | EME |
| 23 | Yadav et al. 2019 | SME | N/A | EME |
| 24 | Zarinah et al. 2017 | SME | Discrete | EME |
| 25 | Iranmanesh et al. 2019 | LE | Process & Discrete | EME |
| 26 | Shafiq et al. 2017 | N/A | Process | EME |
| 27 | Vijay R. Kannan and Keah-Choon Tan 2015 | SME, LE | N/A | Advanced |
| 28 | Belekoukias et al. 2014 | SME, LE | Process & Discrete | All over |
| 29 | Juan A. Marin-Garcia and Tomas Bonavia (2014) | N/A | Process | Advanced |
| 30 | Shashi et al. 2019 | SME | Process | EME |

SME: Small and Medium Enterprises LE: Large enterprises, EME: Emerging market economy

### 3.10.5.1 ILM moderated by industry type

As seen in Table 16 below, the aggregate ILMP-OP association (H3a) is strongly (i.e., positive and significant) influenced by the type of industry implementing ILM ($r=0.795$). In these industry types, the process industry heavily influences the ILMP-OP relationship ($r=0.912$, $p<.001$) followed by when firms are of mixed types (process and discrete) at ($r=0.769$, $p<.001$) and then discrete only firms ($r=0.512$, $p<.001$). This can be attributed to the continuous and batch type of processes involved in process type firms as opposed to the complex assemblies in discrete only firms. This is due to the fact that in process manufacturing, process disruptions are rare or non-existent within a single production run or between production runs of identical items (see, for example, Synchrono 2016).

For each of the ILM practices and OP, the industry type affects these relationships in the descending order of TPM-OP ($r=0.999$), SPC-OP ($r=0.999$), Setup time-OP ($r=0.999$), EI-OP ($r=0.819$), Flow-OP ($r=0.856$) and lastly Pull-OP ($r=0.722$). All relationships are significant at ($p<.001$) except the TPM-OP association moderated by the type of industry.

The 95% credibility interval for all the results is seen to narrowly vary from the lowest limit to the upper one except for the TPM-OP association with discrete manufacturing industries, which varied from a negative to a positive correlation (i.e., -0.03< r <0.260). This shows a wide variation from the lower to the upper limit.

To note is that the impact of industry type on the TPM-OP association for discrete industries is non-significant, and the correlation is very low (r=0.088).

**Table 16: ILMP-OP moderated by Industry type under Fixed Effect Model**

| **Variables** | **k** | **ř** | **P-value** | **95% C.I** | **Z-value** | **Std Error** |
|---|---|---|---|---|---|---|
| H3: ILMP→OP | 27 | 0.795 | < .001 | 0.769, 0.820 | 60.7 | 0.0131 |
| Process | 9 | 0.912 | < .001 | 0.873, 0.950 | 46 | 0.0198 |
| Discrete | 6 | 0.512 | < .001 | 0.444, 0.580 | 14.7 | 0.0348 |
| Mixed | 12 | 0.769 | < .001 | 0.729, 0.808 | 38.1 | 0.0202 |
| H3a: EI → OP | 12 | 0.819 | < .001 | 0.805, 0.834 | 111 | 0.00736 |
| Process | 4 | 0.388 | < .001 | 0.348, 0.428 | 19.1 | 0.0203 |
| Discrete | 3 | 0.166 | <.002 | 0.061, 0.270 | 3.11 | 0.0533 |
| Mixed | 5 | 0.901 | < .001 | 0.885, 0.916 | 113 | 0.00798 |
| H3b: Flow → OP | 6 | 0.856 | < .001 | 0.840, 0.873 | 101 | 0.00846 |
| Process | 3 | 0.649 | < .001 | 0.602, 0.697 | 26.7 | 0.0243 |
| Mixed | 3 | 0.885 | < .001 | 0.867, 0.903 | 98 | 0.00903 |
| H3c: Pull → OP | 16 | 0.722 | < .001 | 0.705, 0.739 | 83.1 | 0.00869 |
| Process | 5 | 0.511 | < .001 | 0.479, 0.543 | 31 | 0.0165 |
| Discrete | 4 | 0.374 | < .001 | 0.297, 0.450 | 9.58 | 0.039 |
| Mixed | 7 | 0.835 | < .001 | 0.814, 0.856 | 78.8 | 0.0106 |
| H3d: Set up→ OP | 15 | 0.999 | < .001 | 0.999, 0.999 | 6060 | 1.65E-04 |
| Process | 4 | 0.85 | < .001 | 0.825, 0.875 | 66.8 | 0.0127 |
| Discreet | 5 | 0.317 | < .001 | 0.257, 0.377 | 10.3 | 0.0308 |
| Mixed | 6 | 0.999 | < .001 | 0.999, 0.999 | 6059 | 1.65E-04 |
| H3e: SPC→ OP | 12 | 0.999 | < .001 | 0.999, 0.999 | 9054 | 1.10E-04 |
| Process | 4 | 0.932 | < .001 | 0.918, 0.946 | 130 | 0.00719 |
| Discreet | 2 | 0.346 | < .001 | 0.267, 0.424 | 8.65 | 0.0399 |
| Mixed | 6 | 0.999 | < .001 | 0.999, 0.999 | 9054 | 1.10E-04 |
| H3f: TPM→ OP | 12 | 0.999 | < .001 | 0.999, 0.999 | 6077 | 1.64E-04 |
| Process | 5 | 0.982 | < .001 | 0.978, 0.986 | 463 | 0.00212 |
| Discreet | 2 | 0.088 | 0.145 | -0.03, 0.260 | 1.46 | 0.0604 |
| Mixed | 5 | 0.999 | < .001 | 0.999, 0.999 | 6059 | 1.65E-04 |

#### 3.10.5.2 ILM-OP moderated by firm size

A combined twenty-six studies analyzed this relationship and came up with a very strong correlation ($r=0.987$). The relationship was also significant at ($P<0.001$). SMEs have a high bearing on the ILM-OP association ($r=0.999$) followed by mixed sized samples of firms ($r=0.755$) and then lastly, the large enterprises ($r=0.682$). This implies that the size of the firm has a huge effect on the ILM-OP relationship. This may be because with the varying sizes comes challenges or ease of the implementation of lean manufacturing. For instance, small and medium-sized businesses are thought to be more adaptable and versatile (e.g., Verhees & Meulenberg, 2004). This may give SMEs an advantage despite resource constraints to yield successful performance outcomes. Large businesses, on the other hand, are more likely to gain stagnation, which might hamper their ability to adjust to new conditions (Boeker, 1997).

For each of the ILM practices impacting operational performance, the firm size affects the relationship in the descending order of TPM-OP ($r=0.999$), Flow-OP ($r=0.866$), EI-OP ($r=0.854$), Pull-OP ($r=0.723$), SPC-FP ($r=0.697$) and lastly Setup time-OP ($r=0.546$).

And for all the relationships, they are affected by moderating factors significantly at $p<.001$.

This means that firm size will have a very big positive and significant impact when moderating total productive maintenance and operational performance compared to other ILM practices.

The 95% credibility interval for all the results varies narrowly within the lowest and upper limits.

**Table 17: ILMP-OP moderated by firm size under Fixed effect model**

| Variables | k | ř | P-value | 95% C.I | Z-value | Std Error |
|---|---|---|---|---|---|---|
| H3: ILMP→OP | 26 | 0.987 | < .001 | 0.96, 0.999 | 73 | 0.0135 |
| SMEs | 4 | 0.999 | < .001 | 0.999,0.999 | 64.8 | 0.0294 |
| LEs | 5 | 0.682 | < .001 | 0.616, 0.748 | 20.2 | 0.0337 |
| All Sizes | 17 | 0.755 | < .001 | 0.721, 0.788 | 44.2 | 0.0171 |
| H3a: EI → OP | 11 | 0.854 | < .001 | 0.840, 0.868 | 121 | 0.00706 |
| SMEs | 2 | 0.384 | < .001 | 0.319, 0.450 | 11.5 | 0.384 |
| LEs | 2 | 0.656 | < .001 | 0.597, 0.715 | 21.8 | 0.0301 |
| All Sizes | 7 | 0.889 | < .001 | 0.875, 0.904 | 120 | 0.00744 |
| H3b: Flow → OP | 5 | 0.866 | < .001 | 0.849, 0.883 | 101 | 0.00858 |
| SMEs | 1 | | | | | |
| LEs | 1 | | | | | |
| All Sizes | 3 | 0.874 | < .001 | 0.850, 0.897 | 73.1 | 0.012 |
| H3c: Pull → OP | 15 | 0.723 | < .001 | 0.705, 0.741 | 79.6 | 0.00909 |
| SMEs | 2 | 0.434 | < .001 | 0.351, 0.517 | 10.3 | 0.0422 |
| LEs | 4 | 0.61 | < .001 | 0.561, 0.659 | 24.3 | 0.0251 |
| All Sizes | 9 | 0.758 | < .001 | 0.738, 0.777 | 75.6 | 0.01 |
| H3d: Setup→ OP | 16 | 0.546 | < .001 | 0.511, 0.582 | 30.2 | 0.0181 |
| SMEs | 1 | | | | | |
| LEs | 5 | 0.483 | < .001 | 0.417, 0.549 | 14.3 | 0.0337 |
| All Sizes | 10 | 0.841 | < .001 | 0.792, 0.889 | 33.9 | 0.0248 |
| H3e: SPC→ OP | 12 | 0.697 | < .001 | 0.657, 0.737 | 33.9 | 0.0205 |
| SMEs | | | | | | |
| LEs | 3 | 0.546 | < .001 | 0.463, 0.629 | 12.9 | 0.0423 |
| All Sizes | 9 | 0.744 | < .001 | 0.698, 0.79 | 31.6 | 0.0235 |
| H3f: TPM→ OP | 11 | 0.999 | < .001 | 0.999, 0.999 | 6047 | 1.64E-04 |
| SMEs | 1 | | | | | |
| LEs | 3 | 0.708 | < .001 | 0.660, 0.756 | 28.9 | 0.0245 |
| All Sizes | 7 | 0.999 | < .001 | 0.999, 0.999 | 6076 | 1.64E-04 |

Note: Blank spaces indicate insufficient data to carry out further analysis.

### 3.10.5.3 ILM-OP moderated by type of economy

It was found out that the success for the application of lean manufacturing would vary in every country or region based on the level of economic development that exists in that country or region.

This can be partly attributed to the organization culture prevailing in a given economic type or country. It could be the potential and ability to train and attract skilled labor. It could be the amount of resources available in a given economy setting or the level of technology and automation. These are all different drivers of lean manufacturing. (Mackelprang and Nair 2010).

As shown in table 18, the type of economy has a very strong positive and significant impact on the ILMP-OP relationship ($r=0.942$, $P<0.001$). It can be further deduced that emerging market economies have a very strong positive and significant influence on the ILM-OP association ($r=0.999$, $P<.001$) than advanced economies ($r=0.781$, $P<.001$). This can be partly explained by a report by the IMF (2016) report which attested to a high manufacturing revolution riddled with cut-throat competition for both domestic and external markets for firms found in emerging market economies which are mostly found in Asia pacific. Almost the world's critical supply chains are within these regions, and there has been increasing offshoring of companies from the advanced economy countries to emerging economy countries (World Economic Outlook Database, October 2016) as such competitiveness arises hence the heightened need for more production techniques like ILM to streamline production and achieve high operational excellence.

For each of the ILM practices on operational performance, the economy type affects the relationship in the descending order of TPM-OP ($r=0.999$), SPC-OP ($r=0.999$), Flow-OP ($r=0.861$), EI-OP ($r=0.766$), Pull-FP ($r=0.726$), and lastly Setup time-OP ($r=0.490$). The relationships are all significantly affected by the moderating factors at $P<.001$.

The 95% credibility interval for all the results are seen to narrowly vary within upper and lower limits.

**Table 18: ILMP-OP moderated by Economy type under Fixed effect**

| Variables | k | ř | P-value | 95% C.I | Z-value | Std Error |
|---|---|---|---|---|---|---|
| H3: ILMP→OP | 29 | 0.942 | < .001 | 0.918, 0.965 | 77.9 | 0.0121 |
| Emerging Market | 21 | 0.999 | < .001 | 0.999, 0.999 | 11656 | 8.57E-05 |
| Advanced Economy | 8 | 0.781 | < .001 | 0.764, 0.799 | 86.7 | 0.00901 |
| H3a: EI → OP | 13 | 0.766 | < .001 | 0.075, 0.781 | 96.2 | 0.00796 |
| Emerging Market | 10 | 0.633 | < .001 | 0.61, 0.656 | 53.1 | 0.0119 |
| Advanced Economy | 3 | 0.873 | < .001 | 0.852, 0.894 | 81.6 | 0.0107 |
| H3b: Flow → OP | 5 | 0.861 | < .001 | 0.844, 0.879 | 97.8 | 0.00881 |
| Emerging Market | 3 | 0.613 | < .001 | 0.562, 0.664 | 23.6 | 0.0259 |
| Advanced Economy | 2 | 0.999 | < .001 | 0.999, 0.999 | 30.6 | 0.0461 |
| H3c: Pull → OP | 15 | 0.726 | < .001 | 0.709, 0.743 | 82.7 | 0.00878 |
| Emerging Market | 12 | 0.528 | < .001 | 0.502, 0.554 | 39.5 | 0.0134 |
| Advanced Economy | 3 | 0.877 | < .001 | 0.854, 0.900 | 75.2 | 0.0117 |
| H3d: Set up→ OP | 16 | 0.49 | <.001 | 0.454, 0.525 | 26.7 | 0.0183 |
| Emerging Market | 12 | 0.477 | <.001 | 0.431, 0.524 | 20.1 | 0.0183 |
| Advanced Economy | 4 | 0.508 | <.001 | 0.451, 0.564 | 17.6 | 0.0289 |
| H3e: SPC→ OP | 12 | 0.999 | < .001 | 0.999, 0.999 | 9054 | 1.10E-04 |
| Emerging Market | 8 | 0.0152 | < .001 | 0.644, 0.703 | 44.4 | 0.0152 |
| Advanced Economy | 4 | 0.999 | < .001 | 0.999, 0.999 | 9054 | 1.10E-04 |
| H3f: TPM→ OP | 11 | 0.999 | < .001 | 0.999, 0.999 | 6077 | 1.64E-04 |
| Emerging Market | 9 | 0.982 | < .001 | 0.978, 0.986 | 456 | 0.00215 |
| Advanced Economy | 2 | 0.999 | < .001 | 0.999, 0.999 | 6060 | 1.65E-04 |

### 3.10.6 Outlier and sensitivity analyses

An outlier analysis of the thirty studies in the research was performed to ascertain if studies with seemingly very high and low correlations from the rest of the other studies were an anomaly and that they skewed the meta-analytical results (i.e., the summary effect size and heterogeneity estimates) to become skewed (Grinstein, 2008, Geysken et al., 1998).

Five percent of the studies at each extreme end of the effect-size values were excluded in this outlier and sensitivity analysis (i.e., the three highest and the three lowest correlations in the current dataset). That is to say, 10% of the thirty (30) studies yield three studies. By splitting these three studies, we obtain 1.5 studies. This was rounded off to the nearest whole number of two, and hence we included the two studies with the highest correlation and the other two with the least correlation. A meta-analysis on the remaining twenty-six (26) studies with 6,332 firms as the sample size was then performed. The four studies dropped from the analysis included (Khanchanapong et al., 2014; Kannan and Tan, 2015; Panwar et al. 2017; Yadav et al., 2019). A meta-analysis with the remaining 26 studies produced an effect size of r= 0.647 with a 95% CI ranging from r=0.587 to 0.707, which is slightly more than the value of r=0.637 with the 95% credibility interval in the range ($0.560<r<0.714$) obtained with the entire set of thirty studies. The minuscule difference in the two summary effect size values of 0.01 (i.e., $0.007<r<0.027$) demonstrates that our outlier correlations did not significantly affect the meta-analysis results.

**Table 19: Outlier and sensitivity analysis summary results**

| | k | N | Outlier correlations (ř) | Correlation (ř) | 95% CI (Lower, Upper) |
|---|---|---|---|---|---|
| Original studies | 30 | 7,075 | | 0.637 | 0.56, 0.714 |
| Outlier studies | 4 | 743 | Hi: 0.999, 0.999<br>Lo: 0.223, 0.108 | | |
| Studies without outliers | 26 | 6,332 | | 0.647 | 0.587, 0.707 |
| Difference | | | | 0.01 | 0.007, 0.027 |

k-number of studies, N- sample size of firms, **ř**- corrected correlation CI- confidence interval

### 3.10.7 Test for publication bias.

The publication bias, also known as the file drawer problem, occurs when researchers conceal or withhold papers that produced non-significant results in their files rather than forwarding them to journals for scrutiny and possible publication. It also covers the publisher' inclination to ignore any studies that produce results of such kind (i.e., negative and non-significant results). This is regarded as a scenario of incomplete data (see Cooper 2010).

The assessment for publication bias, otherwise known as the "file–drawer problem," was done using two known methods, i.e., the Classic failsafe N and the funnel plot.

#### 3.10.7.1 Classic fail-safe N

This is the minimum number of undetected studies with zero and/or negative effect sizes that would be required to cause a change in the final results of a meta-analysis study. A small fail-safe N suggests that the eventual result of the meta-analysis may represent the presence of publication bias.

Rosenthal (1979) proposed calculating the 'fail-safe N' to examine the possibility of publication bias impacting meta-analysis results. This fail-safe N alluded to by Rosenthal (1979) indicates the number of auxiliary negative studies in which there is no impact of intervention i.e., (it has a zero effect) that when introduced in the meta-analysis would lead to a non-significant result of $p > .05$. According to studies (e.g., see Iyengar 1988), the estimate of fail-safe N is heavily dependent on the unpublished studies' anticipated mean intervention outcome. When analyzing the standard fail-safe N, most of the existing approaches produce substantially different estimates of the number of additional experiments (Becker 2005).

According to Borenstein et al. (2009), the classic fail-safe N as an approach to resolving the presence of the publication bias assumes that the results of the meta-analysis usually exclude studies with smaller effect sizes and that if all the excluded or missing studies were to be retrieved and added in the analysis, the p-value of the summary effect size would no longer be significant.

For this concern, according to Rosenthal (1979), the number of missing studies required to render the p-value non-significant should be computed. With the presumption that the mean effect of the missing studies is zero, a classic fail-safe N result that indicates the need for only a few studies to make the effect non-significant implies that the true effect was zero which is a concern to our computations. However, if a vast number of research papers are required to neutralize the effect, the reason to be concerned would be at a very low point or literally non-existent (Borenstein et al., 2009).

Taking a cue from (Rosenthal, 1991), using the results from the Stouffer combined test, the fail-safe number, N can be computed using the formula;

$$N_{fs} = \frac{k x (k x z^2 - 2.706)}{2.706}$$

where k is the number of studies and z is the combined standard z-value for the meta-analysis.

The presence or absence of the file-drawer problem can be determined by comparing the fail-safe value, $N_{fs}$, with the critical number of studies, kc, that can be filed away. i.e., if $N_{fs} > k_c$- there's no file-drawer problem, and if $N_{fs} < kc$, the file drawer problem is then present (e.g., see Clark-Carter 1997; Rosenthal 1991)

Critical number of studies, $k_c = (5xk) + 10$, (see, Rosenthal 1991: 262)

From the meta-analysis values, $k = 30$ and $z = 16.2$

Therefore, by computations: $N_{fs} = 87{,}256.03$ and $k_c = 160$

Since Nfs>kc, it can be concluded that there is the absence of the file drawer problem in our study.

This also means that an average of 2,908 studies (i.e., 87,256 fail-safe N results split by the 30 included studies) disclosing null findings would be required for each of the thirty studies of the current research to render the results of our findings non-significant. It's quite implausible that a great number of studies with such large sample sizes revealing negative or zero associations went unpublished in the literature. Also, any trace of publication bias that may occur anywhere is greatly limited by the substantive and statistically significant result attributed to the final effect size.

#### 3.10.7.2 Funnel plot

The Jamovi software generates two types of funnel plots in this approach. Figure 8 shows a plot of standard errors vs. correlation coefficient for the ILMP–OP interaction. The vertical axis represents study standard errors, whereas the horizontal axis represents z-transformations.

Studies with bigger samples and, as a result, greater precision are placed near the top of the funnel plot. These studies are closer to the vertical line in the middle (indicating the summary effect size) than studies with smaller samples (i.e., less clarity), which lie near the bottom of the funnel. The latter (studies with smaller samples) are scattered more sparsely from or around the average effect size, as shown in the funnel. The middle vertical line splits the plotted values to the left and right based on the magnitudes of particular coordinates, and a circular shape reflects the summary effect size of r=0.637 in each of the plots.

There is no publication bias when the funnel is symmetrical. Likewise, the reverse is true when the file drawer problem exists, i.e., the funnel is asymmetrical (for example, see Duval and Tweedie, 2000a; 2000b). Therefore this allows for the conclusion that the symmetrical distribution of the studies around the mean effect size highlights the absence of publication bias, as shown in figure 10.

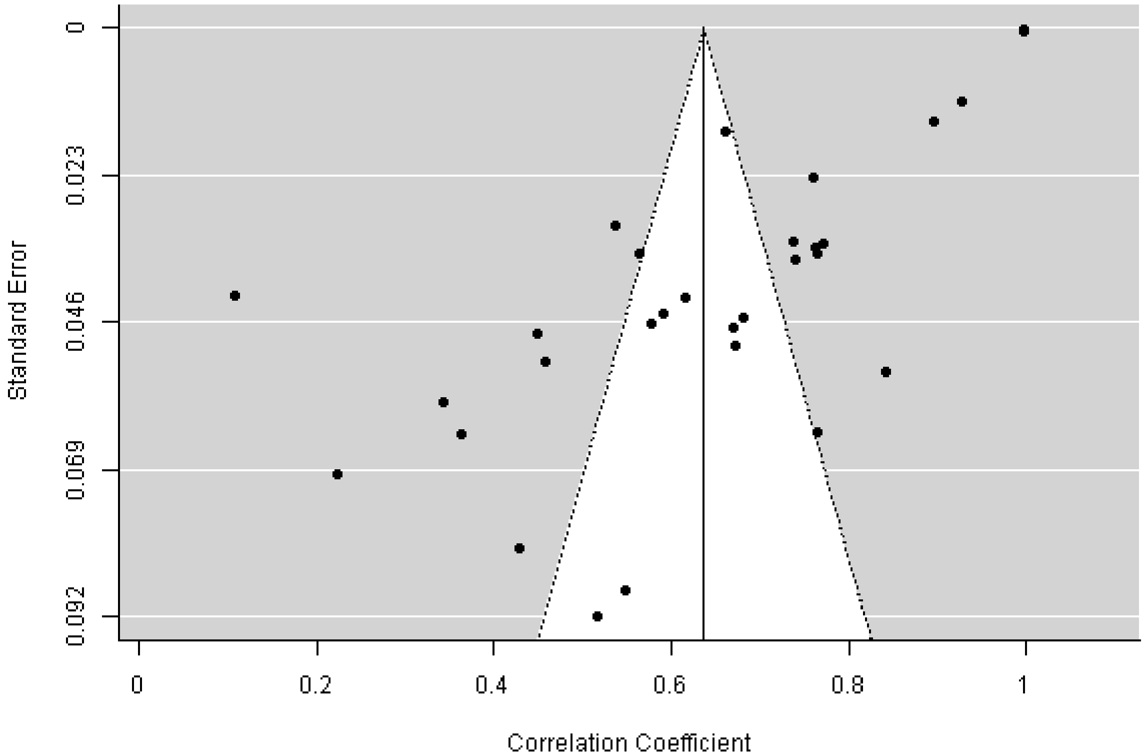


**Figure 10: Funnel plot for publication bias assessment**

### 3.11 Summary

The chapter gives results from the meta-analysis performed on the thirty studies to get a summarised effect size to give us a generalized conclusion on the effect of ILMP on operational performance.

Results from the coding of the information retrieved from each of the studies are also presented in figures and tabulated formats.

Results of the three major and twenty-one sub hypothesis, the heterogeneity results, the sensitivity and outlier analysis results, and the test of publication bias in the study

Interpretations and deductions of the results followed up every analysis to explain the reasons for the achievement and deviation from the expectations. The next chapter presents explanations on the findings, gives a generalized view, raises important questions and advice for future research and the limitations of the study.

# SUMMARY, CONCLUSION, AND RECOMMENDATIONS

## In summary

The purpose of this study was to determine the impact of internal lean manufacturing practices on manufacturing organizations' operational performance. To investigate this link, the researcher used a meta-analysis approach based on a sample of thirty papers published between 2010 and 2020. In order to answer the research questions and test hypotheses based on the relevant literature, the meta-research approach and research design were established and implemented. This chapter, therefore, contains a summary of the thesis, the conclusions, and implications from the study findings, as well as suggestions for future research.

## Introduction

Lean manufacturing has over 48 tools which Shah and Ward (2003) first divided into twenty-two practices and then broke this twenty-two further into four practices, i.e., HRM, JIT, TPM, and TQM. Many authors have taken different angles to explore lean manufacturing, and as a result, there are many ways LM has been defined according to which practices a particular study adopts. However, the Shah and Ward (2007) proposed model has been the baseline for each of the research studies on LM done by different researchers all over the world. It is hence, for this reason, that this study adopted and used the internally related constructs suggested in Shah and Ward (2003) model.

Lean manufacturing is such a wide subject with structural, external, and internal divisions. For clarity and specificity, internal lean manufacturing was adopted, and its impact was tested on operational performance for this study based on Shah and Ward (2003) proposed model and definitions. Because each of these divisions carries different lean practices, therefore distinguishing between these dimensions or principles of ILM provides a better understanding of the effects of each of them under the aggregate ILM on operational performance outcomes of the firm.

Literature containing many and unique theories has been developed by the few scholars that investigated the ILMP-OP relationship. And as a result, either similar or different generalizations have been reached in the different cases. It cannot be outrightly stated that the case of ILMP-OP is settled and that its conclusion always points to the same and consistent outcome. Taking this into account acted as a trigger for the need for further exploration of ILMP-OP association by looking at many of the convergent and divergent studies to try to establish common ground and add to the already existing literature in the domain of lean manufacturing and understand how it influences the operational performance of manufacturing firms.

An appropriate method selected to carry this out was a meta-research that combined past and recent empirical primary studies with clear definitions, measures, and theoretical basis to aid in providing a good basis for future related studies. Identifying and establishing via previous studies which practices are effective in determining the link between ILMPs and operational performance will be of great help to both practitioners and researchers.

Incorporating lean manufacturing on the production shop floor has been discovered as a recipe for increased production efficiency, bringing down costs, generating value for the firm and customers as well as augmenting employee motivation and satisfaction, and consequently, the firm’s overall performance.

Because of the evolving nature of manufacturing on the shop floor spurred by innovation, invention, industrialization, technology, and information, internal lean manufacturing has been affected as well. As a result, many more studies have poured in to try to update and explore more of the changing ILMP-OP relationship. With these studies comes the different conclusions, new theories and concepts, new discoveries, and the different angles in which lean manufacturing has evolved. Everything about the studies carried out is almost consistent in that new theories are found and contribute to the bank of the already existing theories. However, what is inconsistent about these studies is the general lack of consensus on these primary, earlier and recent studies on the LM-OP relationship. This, therefore, leaves room for another meta-analysis to help fill this void in a bid to help settle the ILMP-OP question where an end in sight has proven elusive.

The meta-analysis was carried out with a host of different moderators to try and test if the inconsistency in the results was due to the application of lean in different conditions.

Thus, this research attempted to address the divergences and improve on earlier reviews by taking into consideration recommendations for better meta-analyses highlighted in previous studies or reviews. Against this backdrop, thirty studies from 2010 to 2020 were included in determining if new insights, consensus, and clarity are achieved on the topic. This meta-analysis attempts to clarify theory and contribute to the field by adding recent studies with known moderators. As an attempt to address these issues, the following research questions and objectives were developed as follows:

**Research objectives and research overview**

These objectives are in response to the research questions and the issues raised in this study

• To determine whether there is a link between internal lean manufacturing and operational performance.

• To determine the extent to which ILM's six practices impact operational performance.

• To determine which of the six practices of ILM has the most significant impact on operational performance.

• To figure out which critical moderators have a big influence on the ILM-OP relationship

To address each of these research objectives and consequently settle the research questions raised, a comprehensive critical review and understanding of lean manufacturing literature were done.

This enabled the researcher to get introduced to the different definitions of lean manufacturing, the divisions inside LM, the detailed explanation of six practices of ILM, the ILM-OP relationship, internal lean, operational metrics and measures, hypotheses development, and the research model.

Based on the works of earlier researchers in the sphere of lean manufacturing, most particularly Shah and Ward (2003), a theoretical framework was developed that defined lean manufacturing as a production methodology that maximizes productivity within the manufacturing systems while minimizing waste. This is achieved in concert with the selected six lean practices from the forty-eight (48) practices proposed by Shah and Ward (2003) that include total productive maintenance, continuous flow production, statistical process control, continuous flow production, statistical process control, pull production, employee involvement, and setup time reduction.

From the different conceptual frameworks developed for lean manufacturing, there is a wide-ranging array of performance types and dimensions, i.e., financial, market, competitive growth, business, and environmental performance, written on and analyzed against lean manufacturing implementation. The dimensions such as sales growth, rate of return on investments, net present value, customer retention, customer satisfaction, quality performance, inventory turnover, employee satisfaction, raw materials delivery, production flexibility, lead time, return on assets, etc., were noted to have taken a bulk of space in the performance types suggested or used. However, for this study, performance was looked at from an angle of only operational performance which includes nine metrics, namely first pass yield, production flexibility, waste minimization, manufacturing costs, on-time delivery, high product quality, reduced defect rates, increased productivity, and reduced lead time.

Three moderating factors, i.e., size of the firm, the sector in which the industry falls, and the type of economy, were chosen and tested on the two major categories of hypotheses developed (aggregate ILM-OP and individual ILM practices-OP) and the 22 sub hypotheses. The rest of the 22 sub hypotheses focussed on the impact of the moderating factors on the six ILM practices. From here, a research model indicating all these associations mentioned was developed.

To achieve all the above and to confirm the developed hypotheses, the search and retrieval of relevant studies from theses, articles, conference papers, and other online study material from Google academic and other sites published from 2010 to 2020 was done from both online and manual databases. Through a stated inclusion and exclusion criteria, the suitability of the collected studies was determined, whereupon thirty studies were arrived at. Of the 605 studies gathered, 551 were dropped because they were outside the inclusion criteria leaving 50 studies to be further scrutinized. Of these, 30 were used for the final meta-analysis computations, but the rest of the 20 were also referred to regularly because of their rich literature on lean manufacturing, particularly on the specific internal lean.

By following the meta-analysis review of the way of Hunter and Schmidt (2004) with the aid of the Jamovi software, this study was conducted after the correction of sampling and measurement errors. The Jamovi software was chosen over other meta-analysis software because of its being open-source and free-to-use software, simple, and its ability to provide all the necessary meta results accurately.

Each of the included studies from the whole lot of thirty studies contributed one effect size (correlation coefficient) to this meta-research with a combined sample size of 7,075 manufacturing firms. This study focussed on 100% manufacturing firms (process and discrete manufacturing), with the most firms (4,032) registered in the emerging market economies (Asia Pacific), and it was analyzed statistically mostly by a combination of regression and correlation analysis (27%).

A heterogeneity test was made and successfully passed before proceeding further with the meta-analysis. This test had all the proposed hypotheses heterogeneously significant, thereby clearing the way for the use of the random effect model (RE) over the fixed-effect (FE) and the need to try or test the three proposed moderator factors on all the twenty-four developed hypotheses in the study.  A positive and significant result was established from the ILMP-OP link, as was the case for all the six practices under ILM when tested on operational performance except for the TPM-OP relationship moderated by discrete manufacturing firms, which was non-significant.

From the results of the moderator analysis, all the relationships analysed were positively strongly and significantly influenced by all the moderating variables. Now with all the three major research questions duly answered,  it can be stated confidently that all the research objectives were successfully achieved.

**Conclusion**

From the conceptual framework, results, and findings of this meta-correlation research, a number of conclusions can be made. Additionally, from the outcomes of the tested hypotheses, more conclusions can be reached.

Taking the objectives into account and the research questions raised, three main categories of conclusions for example; (i) those that are based on aggregate ILM-operational performance relationship (ii) those based on individual ILM practices and operational performance, and (iii) those that are based on the effects on moderators on all the relationships were reached.

In the first category, the conclusion that can be made from the test of hypothesis one (H1) is that aggregate ILMPs possess a positive and substantial influence on the operational performance of manufacturing firms. The meta-analysis results specifically produced a coefficient of correlation of $r=0.637$ and a p-value of $<0.001$, signaling the association isn't only positive but also strong and significant. In the second set tasked with testing hypothesis two (H2), the following conclusions can be drawn, for example i) Total productive maintenance is strongly associated with operational performance. The association is also significant i.e., ($r=0.643$, $p<0.001$), ii) Setup time reduction has a medium and significant association with operational performance ($r=0.424$, $p<0.001$), iii) Statistical process control has a strong and significant ($r=0.584$, $p<0.001$) relationship with operational performance, iv) Continuous flow production with a strong positive correlation significantly influences operational performance, i.e., ($r=0.682$, $p<0.001$), v) Pull production has a medium and significant influence on operational performance, i.e., ($r=0.409$, $p<0.001$) and lastly vi) Employee involvement has a medium significant relationship on operational performance, i.e., ($r = 0.449$, $p<0.001$)

Since all hypotheses (H2a-H2af) were positive and significant, hypothesis (H2) is accepted thus, allowing for the conclusion that all ILM practices influence operational performance. This is consistent with studies (e.g., Chavez et al. 2013; Sezen et al. 2012; Shah & Ward 2003) that also established that all the named six internal lean manufacturing principles had a positive and that all the six internal lean manufacturing practices had a positive and significant influence on the operational performance.

Regarding the effect of moderators on the ILM-OP relationship, the subgroup analyses conducted under the fixed-effect model show that all the relationships analyzed were positively and significantly affected by the moderating variables, although to a varying magnitude. The results point to the size of the manufacturing firms affecting the aggregate ILM-OP association more than other moderating variables, type of the economy and the type of industry. And from the size of the industry, it was revealed that the SMEs had the largest impact than the large enterprises ($r=0.999$ against $r=0.682$ respectively). This implies that the smaller the firm becomes, the more the performance outcomes will be reaped out of implementing internal lean manufacturing. This can be explained that as the firm size expands, the more complexities of management surface, i.e., that smaller firms are more agile with simpler processes than LEs (Verhees and Meulenberg 2004). Conversely, the larger firms are expected to have a large resource base which they can allocate to the lean implementation program (Schilke, 2014).

As for the ILMP-OP moderated by industry type, process-type industries were observed to impact the relationship more than the discrete-type industries. This is consistent with the findings of Panwar et al. (2015) and White & Prybutok (2001), which established that lean manufacturing techniques were more important for the performance of process-type industries than discrete-type industries. This finding can be attributed to the batch and continuous nature of production in process industries which ensures minimal interruptions within a set production run or in between the production runs of related products as opposed to the complex assemblies in discrete firms (Abdulmalek et al. 2006). Additionally, production in process industries involves fewer steps than in discrete manufacturing. Therefore, less inventory accumulates than it does at the many multi-stage/assembly points of the discrete manufacturing (see Floyd, 2010; Panwar et al., 2015). It is also understood that since process-type industries, e.g., beverage industries, consume lesser amounts of raw materials while producing more quantities of products, this makes them highly dependent on the high availability, operability, and reliability of machinery, which is achieved majorly by lean manufacturing practices such as TPM and Kaizen (Abdulmalek, Rajgopal, and Needy, 2006).

For the type of economy, firms from emerging markets were observed to largely impact the ILMP-OP relationship. This can be partly explained by a report by the World Economic Outlook Database (October 2016), which found increasing manufacturing activity in emerging market economies, especially the Asia Pacific. Also, the world's critical supply chains are within these regions as there has been increased offshoring of operations of companies from the advanced economies to the emerging economies due to cheap labor, cheap raw materials, low tax regimes, less unionization, less regulations, and a favorable organizational culture like the industriousness of the labor. This Asia Pacific region is also boosted by a rising productive population which stands at over 4.68 billion, accounting for nearly 60% of the global population (see world meter report, 2019). This is among the reasons why many manufacturing plants have shifted operations in this region to benefit from the abundant and cheap labor made possible by the less unionization and low wages here than in the advanced economies. The emergence of the Asia Pacific region cannot be overemphasized as a report by Mckinsey global institute, "*The future of Asia, 2019,*" analyzing the patterns of the economy of Asia for 18 years for the period between 2000 and 2017 found a rise in the share of the global consumption from 23% to 28% attributed to Asia alone, a 23 percent to 40 percent increase in the number of people in Asia transitioning from the lower into the middle class and a 32 percent to 42 percent increase in its share of the global Gross Domestic Product (GDP) assessed in terms of purchasing power parity (PPP). This report further projects that the outlook on all these factors will continue on a linear trajectory to 39%, 54%, and 52%, respectively, in the year 2040. Such positive industrial indicators are enablers or attractors of more investments which may come in the form of more venture capitalists for start-ups and more manufacturing firms established, which may, directly and indirectly, influence the deployment of lean manufacturing if businesses in this region start to compete with each other (see Mckinsey Global institute 2019 report, “The future of Asia.”)

And for each of the six internal lean practices drawn against operational performance, analysis of results indicate that total productive maintenance was the most affected across all the three moderating factors with a very strong correlation ($r=0.999$) and a significant relationship. This implies that no matter the size, the type, and the economy in which the firm operates, the results or influence as regards the TPM-OP relationship will remain the same.

However, in one rare finding, there was a very dismal correlation ($r=0.088$) and a non-significant ($p<.145$) relationship of the TPM-OP relationship moderated by the discrete manufacturing industry. This came as no surprise owing to the nature of discrete manufacturing, which involves large assemblies, automation, and batch production. However, this is a subject of further investigation to ascertain if this result is consistent throughout other studies done or it is just an outlier.

For the six ILM practices, by averaging their correlations across the three moderators, a summary of how their relationship with OP was affected when tested on the three moderating factors is as follows: i) TPM-OP relationship is positively and significantly affected across all the three moderating factors, i.e.,($r=0.999$, $p< 0.001$), ii) SPC-OP relationship is positively and significantly affected across all the three moderating factors, i.e., ($r =0.898$, $p< 0.001$), iii) Set up time reduction-OP relationship is positively and significantly affected across all the three moderating factors, i.e., ($r =0.678$, $p< 0.001$), iv) Employee Involvement-OP relationship is positively and significantly affected across all the three moderating factors, i.e., ($r =0.813$, $P< 0.001$), v) Pull Production-OP relationship is positively and significantly affected across all the three moderating factors, i.e., ($r =0.724$, $P< 0.001$), vi) Continuous flow production-OP relationship is positively and significantly affected across all the three moderating factors, i.e., ($r =0.861$, $P< 0.001$)

It can be summarily deduced that the ILMP-OP is impacted by all three moderators in the descending order of magnitude of the relationships TPM-OP followed by SPC-OP, continuous flow production-OP, employee involvement-OP, pull production-OP, and lastly setup time reduction-OP.

**Discussions**

In table 20, the summary of results from all the hypotheses developed is shown. The major and all sub-hypotheses developed from the research are observed to be supported.

**Table 20: Summary hypothesis results**

| Relationship | Main Hypotheses | Is the relationship positive and significant? Moderating factors | Industry type | Industry Size | Type of economy |
|---|---|---|---|---|---|
| H1: ILMP→OP | Yes | Yes | Yes | Yes | Yes |
| H2a: Employee involvement → OP | Yes | Yes | Yes | Yes | Yes |
| H2b: Flow production → OP | Yes | Yes | Yes | Yes | Yes |
| H2c: Pull production → OP | Yes | Yes | Yes | Yes | Yes |
| H2d: Set up time reduction → OP | Yes | Yes | Yes | Yes | Yes |
| H2e: Statistical Process control → OP | Yes | Yes | Yes | Yes | Yes |
| H2f: Total Prod. Maintenance → OP | Yes | Yes | Yes | Yes | Yes |

The support of all hypotheses, as shown in the table, further cements the position of lean manufacturing as a reliable and time-tested methodology that, when applied successfully, will bring about improved operational performance.

Some of the seven important takeaways from the results of the study paint a picture of continuous flow production having the greatest impact on operational performance, and therefore, its consideration and implementation should be prioritized over other ILM practices. Secondly, when all the six LP practices are aggregated together, the outcome of their effect on OP is slightly higher than the individual relationships of SPC-FP, EI-OP, Pull-OP, Setup-OP but slightly lower than the TPM-OP and continuous flow-OP associations. Thirdly, the total productive maintenance and operational performance relationship are observed to be greatly influenced by the selected moderating factors than any other associations. Fourthly, process-type industries influence all the six associations of ILM-OP and the aggregate ILMP-OP relationship more than the discrete type of industries. Fifthly, it is also found that samples of mixed sizes of firms influenced all the associations greatly than any other category of sizes considered. Sixthly, firms selected from advanced economies are also seen to greatly influence the ILMP-OP association and each of the six ILM practices and OP than the emerging market economy type. Sevenly, the total productive maintenance when applied to discrete industries to influence operational performance is impactless and insignificant. It should therefore not be applied in such a setting, and lastly, all the associations have been discovered to have a high degree of variability. This means these relationships will be affected by different moderators or mediating factors

**Empirical contributions of the research (Managerial, Business, and Academic implications)**

This study, if adopted by scholars or academicians and practitioners such as production managers, plant managers, operations managers, shop floor supervisors, maintenance managers, and project managers, and also scholars will have a substantial effect on their work and their overall organizational performance in terms of operations. Since the main findings it has been revealed that ILM implementation positively and significantly influences operational performance, the adopters of ILM now have a clear understanding and a general picture of what to expect when they successfully implement the six practices of internal lean manufacturing. From the results of the study, the implication is the reaping of the nine operational benefits described in the study.

Additionally, of the six ILM practices, the potential adopters of ILM now know which of the six practices is/are the best predictors of operational performance. This will enable them to plan appropriately and expend resources on the practices where they will reap the highest yields.

From the results of the moderator analysis, the potential adopters of ILM now have clear insight backed by data on the probable situations and their extent of influence when implementing ILM. For instance, it's now clear that emphasis on total productive maintenance and continuous flow production in a small factory setting, in a processing type firm, and in an emerging market economy gives the best operational performance results that can be obtained than any other of the six practices of ILM under the same stated conditions.

For the researchers and future students with interest in lean manufacturing, this study adds to the bank of literature from the previous studies. This literature and knowledge on the same subject of LM come with a different angle of looking at lean internally, which will help widen the scope of theories and literature in this field. More theories and techniques in lean have been explored and added by carrying out this research. This will help future researchers enrich their knowledge as regards lean, particularly the six ILM practices that have been the focus of this research.

Lean manufacturing is believed to also spur improvement or a positive effect on other known common performance types like operational environmental, financial and market performance, employee performance, etc, although the evidence-backed by the data to support this up is still little. As for this research, the statistical analysis has confirmed a positive association of ILMPs on OP. Therefore, this arms LM practitioners with data-backed research to make informed production decisions.

Finally, the outcomes of the individual lean practice evaluations can help firms determine which practices they should hierarchize in order to achieve their specific goals. The study avails some insight on the applicability of particular methods or tools based on the different conditions in which the firms may be operating.

**Implications for theory**

According to Card (2013), a meta-analysis' main goal is to integrate and synthesize prior studies as an essential step in the advancement of scientific and social research or knowledge of a phenomenon or an object of study. From this perspective, the current research has substantial implications for the historical, present, and future of lean manufacturing research.

Total Productive Maintenance (TPM) has been discovered in this study to have no impact on operational performance when applied in discrete manufacturing industries. Future researchers may begin from here to investigate why this is so.

The heterogeneity analysis also reveals that all of the examined associations are very variable. The three moderating factors chosen do not help explain the heterogeneity found, and maybe only the type of economy in which the sample was selected provides just a portion of the explanation. As such, future researchers must set out to find these explanations and can also investigate other contextual elements that could better help give a grasp of the ILMPs (e.g., SPC, EI, continuous flow, Pull production, TPM, and Setup time reduction) impact on OP and probably the wider domain of lean manufacturing.

**Future research, limitations, and recommendations**

Advice for similar future research is provided to give guidance on how to address the limitations and expand on future studies of the same subject.

This study aggregated a total of only thirty studies. Expanding on this number in future research will likely produce a much more generalizable result since it has been found that the more sizable the sample size for the study is, the more reliable its results are.

Again the study may be replicated with inclusion/exclusion criteria that allow for the inclusion of a large number of other moderating factors. This will give a clearer picture of the ILM-OP relationship when set in many and different scenarios. Perhaps it will be interesting to see if the ILM-OP behavior will remain the same or vary across the different moderators.

This study did not look at mediating factors. It is believed that the ILM-OP relationship is not an end in itself but rather facilitated by a host of second and third factors, either directly or indirectly. It will be interesting if further research can add mediating factors to ascertain if there is a change in the results of the ILM-OP association.

This study only explores the impact of ILM on operational performance. Future researchers can widen the scope of research to include as many components of organizational performance as possible such as environmental, financial, market, employee performance, and customer satisfaction, among others.

Furthermore, this research narrowed firm performance to only operational performance, which included nine dimensions. As we know, firm performance is bigger than one measure. It's, therefore, a suggestion that future studies may, in addition to the nine metrics included in the operational performance for this study, also explore other measures of operational performance like inventory turnover, worker turnover, proper scheduling, employee satisfaction, customer satisfaction, supplier relationships, and competitive growth and many others.

A wider language criterion or at least a translation of studies published in other languages like Chinese, French, Arabic, and Turkish should be considered to improve the sample size of the studies.

The generalizability of this paper's findings is mostly controlled by two elements, namely the sample of studies included in the original analysis and the sample of firms, as is the case with most meta-analytic studies. With regard to these two samples, every effort was made to include all relevant papers for this study, but little effort was made to look into any unpublished studies or those in manual databases and studies that produced negative and non-significant results. However, to allay any fears on the robustness of the final result obtained as a result of this inadequacy, a publication bias assessment was run, and it returned results that re-affirmed the robustness of the aggregate results and others. Owing to the fact that the summary effect size was also significant at $p<.001$, this further re-assures that the final result cannot be in any way altered by the exclusion of such kinds of studies. However, these unpublished studies form a very important component of performing any meta-analysis, according to Cook (1993). So, for future researchers, these studies ought to be included.

In terms of the representativeness of the sample of companies examined by the studies included in this study, it can be shown that a significant portion of them are manufacturing businesses. As a result, future researchers must include as many different types of businesses as in the service industry category as much as possible.

The presence of the variance or heterogeneity that can not be explained in the examined relationships necessitates further investigation to assist learners in comprehending the causes of these variances. Due to the lack of data in the studies, it is to analyze moderating factors such as company size, industry type, and economy type. A deeper analysis should delve into these moderator elements, as well as the underlying causes for the variances in the impact of advanced and developing countries, the small and larger firms and the process and discrete type industries, and the effect on the ILMP-OP relationship.

The impact of interdependencies among the six lean productions (LP) factors on operational performance was examined in this study. This can be viewed as a supplement to the meta-analysis research on the relationship between lean manufacturing and organizational success (OP). Future research may focus on the impact of combining a variety of various types of lean manufacturing practice bundles on a variety of firm performance metrics.

It is also imperative that future researchers investigate the duration and magnitude of leanness that companies have to achieve in order to realize an increase in operational performance. This is because lean is implemented following a framework in which a number of processes are involved, and this takes time. Also, lean is a total company-wide approach that requires the involvement of everyone in the organization and requires consistency of application to yield the intended results.

Last but not least, the coding reliability of the replicated study should be improved through the involvement of other researchers, most preferably more than one or two specialists, in the coding process. This would ensure that more accuracy, reliability, and validity of the whole study where no relevant data is left out.

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# APPENDICES

## Appendix 1: Qualitative details for each of the thirty studies included

| Study/Paper | Method | N | Lean practices | Firm performance | Findings |
|---|---|---|---|---|---|
| Panwar et al 2017 | PCA, EFA, Multiple regression analysis | 121 selected process industries in India | Quality control, constraint removal, Quick changeover techniques, Lot-size reduction, 5S, TPM, SPC, Work standardisation, Continuous improvement programmes, pull production, Flexible and cross-functional teams | timely deliveries, productivity, first-pass yield, elimination of waste, reduction in inventory, reduction in costs, reduction in defects and improved demand management. | Lean practices are positively associated with operational and quality performance |
| Khanchanapong et al. 2014 | Bivariate correlations, Structural Equation Modelling | 186 manufacturing plants in Thailand | Prod. Flow Mgt (Set-up time reduction, Pull production) Process mgt(SPC, Continous improvement), customer focus, Workforce Mgt (Employee training, cross functional training, Solution/idea suggestion by all employees) | quality, lead-time, flexibility, and cost | Lean practices haS unique effects on a range of operational performance including quality, lead-time, flexibility, and cost |
| Rahman et al. 2010 | Multiple regression models | 187 Thai manufacturing firms | reducing production lot size; reducing setup time, preventive maintenance, cycle time reduction, quick changeover techniques, pull-based production, Poka-yoke, removing bottlenecks | Quick delivery compare competitor, Unit cost of product relative to competitors, Overall productivity, Overall customer satisfaction | All three lean constructs (JIT, Waste minimisation, Flow management) are significantly related to operational performance. |
| Belekoukias et al. 2014 | Linear regression analysis, Correlation analysis, Structural Equation Model. | 140 manufacturing organisations around the world. | JIT(Pull system),TPM, Automation(Poka-yoke), kaizen(5S, pareto chart, gantt, 5 Whys), (TPM) | Quality, Speed, Dependability lead-time, flexibility, and cost | JIT and automation have the strongest significance on operational performance while kaizen, TPM and VSM seem to have a lesser, or even negative, effect on it. |
| Valente et al. 2019 | Partial least squares–structural equation modelling | 329 Portugeese enterprises | customer involvement, statistical process, continuous flow and total productive maintenance, Pull, Set up time reduction (Setup), Employee involvement, employees undergo cross-functional training | Operational performance(Cycle time, Manufacturing costs, Labour productivity, Quality Inventory Flexibility, Delivery) Financial performance (ROS, ROA, ROI) Profit), Sales growth | The effects of Lean on performance are positive, which stresses the benefits attainable with the implementation of Lean practices. |

| | | | | | |
|---|---|---|---|---|---|
| Marodin et al. 2017 | OLS regression, Bivariate corelation | 64 companies of the Brazilian automotive supply chain | Standardised work, TPM, Problem-solving, Pull production, Set up reduction, production levelling | Lead time, Inventory, Quality On-time, Turnover | Results suggest that Brazilian companies are experiencing reduction of Lead time due to the implementation of TPM practices; and reducing inventory based on the adoption of just-in-time practices |
| Alsmadi et al 2012 | Regression analysis | 143 UK respondents were from the manufacturing sector | Customer involvement, statistical process, continuous flow, Total productive maintenance, Pull, Set up time reduction (Setup), Employee involvement(o cross-functional training, idea suggestion, problem solving groups) | Customer satisfaction, employee satisfaction, cycle time, production cost. return on assets (ROA), market share and labour productivity | The results show a positive relationship between Lean practices and firm performance |
| Sezen et al. 2011 | ANOVA and correlation | 207 Turkey automotive part suppliers | Setup time reduction, Pull production, Preventive maintenance, Employee suggestion system, Error proof equipment, Continuous improvement, '5S', Process improvement, One piece flow | Product quality, Delivery speed, delivery reliability, FP(Sales growth, ROA, mrkt share gain | A significant relationship is found between the lean applications and firm performance. More specifically, there is a stronger relationship between lean techniques and Operational performance as compared to the relationship between leanness and financial-market performance. |
| G.L.D. Wickramasinghe and Vathsala Wickramasinghe 2017 | Hierarchical regression analysis, Correlation analysis | 1,189 respondents from export-based textile and apparel firms in Sri-Lanka | Continuous improvement, Pull, Cross-functional teams, Employee involvement | efficiency of the process, delivery in full on time, accepted quality level (AQL | Lean production practices significantly enhance manufacturing performance |
| Chavez et al 2013 | Correlation analysis, Ordinary least square (OLS)-regression analyses | 228 manufacturing companies in the Republic of Ireland. | Set-up time reduction, JIT(MTO), | quality, delivery, flexibility and cost, Reducing inventory, Production cost) | The relationships between internal lean practices and quality, delivery, flexibility and cost were found to be positive and significant |
| Juan A. Marin-Garciaa and Tomas Bonavia (2014) | Partial Least Squares –Structural Equation Modelling | 101 ceramic tile plants in the Valencia region of Spain. | Empowerment, Group problem-solving, Training on LM practices, pull system, TPM, Reduction in machine change over times, Set-up time reduction, Multi-function employees, Job rotation | Production costs, speed of order completion, Product quality | All paths are significant except for contingent remuneration; specifically, relationships were found between empowerment, training, communication and LM, and between LM and performance. |

| | | | | | |
|---|---|---|---|---|---|
| Negrão et al. 2019 | Partial Least Squares –Structural Equation Modelling, Correlation analysis | 217 plants in Brazil | Pull (Pull), Continous flow, set up time reduction, SPC, problem solving teams, idea suggestion by teams, TPM | OP: Rework, Lead time. Financial Performance(Profitabil ity, SALES, Market share) | The adoption of lean manufacturing practices enables organisations to achieve significant and simultaneous performance improvements in terms of operational, financial and environmental measures; |
| Vijay R. Kannan and Keah-Choon Tan 2015) | Structural equation Modelling (SEM) | 556 surveys in North America and Europe | Reducing setup time, Preventive Maintenance, Statistical process control, Employee training in quality, | a. Market share<br>b. Return on assets<br>c. Overall product quality<br>d. Overall competitive position<br>e. Overall customer service levels | Results show that while just in time, quality and SCM efforts are indeed mutually supportive, it is a firm's efforts in the area of quality mgt that directly drive business performance. |
| Onofrei et al 2019 | Ordinary least square (OLS) models, interfactor correlations | Australia, China, Croatia, Hungary, India, Ireland, Poland, Taiwan, USA, Vietnam. Total: 528 plant responses | Flexible workforce, automation, Manufacturing lead time reduction programmes, Workforce training and development | cost, quality, flexibility and delivery dimensions. Delivery speed, Delivery reliability, Labour unit costs, Total product unit costs, Raw material unit costs | Lean practices investments lead to higher operational performance, specifically in terms of cost, quality, flexibility and delivery dimensions. |
| Al-Zu'bi et al 2015) | EFA, Hierachical regression analyses, Multiple regression analysis | 157 manufacturing companies in Jordan | pull system and continuous improvement, Setup time reduction | flexibility(Product-mix flexibility, Production volume flexibility, On-time delivery, Plant uptime) | A positive and significant effect of lean production on flexibility performance in a developing country |
| Nawanir et al. 2010 | Pearson correlation analysis, Multiple regression analysis, Principal component analysis, and Simple regression analysis | 139 indonesian manufacturing firms | Pull system, Quick Setups(lower machine setup times), Total Productive Maintenance, Statistical techniques are used | quality, flexibility, lead time reduction, and cost reduction. | The evidence provides strong support that the higher extent of lean practices implementation will bring to the better OP |
| Shashi et al. 2019 | Structural equation Modelling (SEM) | 374 manufacturing plants in India | Pull production system, process-set-up time reduction | Process innovation (Decreasing variable cost and/or increasing delivery speed, Increasing output quality, Decreasing variable cost components), FP(RO1, ROA, Profitability, Sales growth, Total operating costs) | The hypothesis which stated that the higher the leanness of SMEs, better the financial performance, was confirmed. The leanness of SMEs positively affects process innovation, A positive impact of process innovation on financial performance strongly emerges in the present study. |
| Chi Phan et al. 2019 | Correlation and regression analysis | 280 manufacturing plants in China, Finland), German, Italy, Israel, Japan), Korea, Spain, Sweden, Taiwan, UK and Vietnam | Use of tools and techniques to monitor the manufacturing process, set up time reduction | Flexibility(Firm's ability to meet customers' flexibility needs. Respond to sudden changes in customer requirements) | A positive linkage between JIT practices, TQM practices, and flexibility performance. Firms will achieve higher ability to meet customer's flexibility needs if they focus strongly on TQM and JIT. |

| | | | | | |
|---|---|---|---|---|---|
| Wickramasinghe and Perera, 2016 | Correlation and regression analysis | 30 Sri Lankan export oriented textile and apparel manufacturing firms | TPM(Education and development, Individual improvement, Planned maintenance, | cost effectiveness, product quality, on-time delivery and volume flexibility. | The results show that all the TPM practices have positive and significant relationship with manufacturing performance and significantly improve cost effectiveness, product quality, on-time delivery and volume flexibility. |
| Chavez et al. 2015 | Structural equation modeling and OLS regression analysis | 228 manufacturing companies in the Republic of Ireland | Set-up time reduction, JIT(Pull) | Production cost, High product performance, Delivery on due date, Reducing production lead time, FP (ROI), Profit margin | A significant impact of ILP on operational performance and organizational performance. |
| Sahoo (2019) | Structural equation Modelling (SEM) | 148 Indian manufacturing firms | Total employee involvement, Total productive maintenance, JIT, TQM | Productiity, cost, quality, delivery, flexibility | lean practices are positively related to business performance parameters |
| Sahoo & Yadav 2017 | correlation, SPSS | 121 indian manufacturing industries | statistical quality control, statistical process control, cross functional training, employee training | Process quality<br>▪ Product quality<br>▪ Customer satisfaction | TQM positively affects firm performance |
| Costa et al. 2020 | Structural equation Modelling (SEM) | 145 food industry firms in Brazil and USA | Continous flow, employee involvement(problem solving teams, employees drive suggestion programs, cross fuctional training), set up time, TPM, SPC, Pull | Productvity, product quality, reduced lead time, losses reduced | Food industry performance is positively affected by the adoption of LSS practices. |
| Saini & singh (2019) | Correlation, regression, canonical analysis and ANOVA | 183 Northern India SMEs | TPM, Training teamwork, employee involvement, SPC, set up time reduction, cellular lay-out, kaizen/JIT | Quality, cost, delivery, Productivity, profitability | It is revealed that total productive maintenance, supplier management, just-in-time and five S practices enhance the firm performance. |
| Nawanir et al 2013 | Multiple regression and Correlation analysis | 139 respondents from Indonesian manufacturing companies | small-group problem solving, multi tasking, Cellular layouts, Pull, setup time reduction, SPC, TPM, | Product cost, delivery, productivity, Cost, Prtofitability, | Lean practices have a positive and significant impact on both OP and BP |
| Yadav et al 2019 | Structural equation Modelling (SEM) | 425 SMEs in India | employee involvement, pull system, 5S, TPM, statistical process control (TPM), Set up time reduction | Production cost, Productivity, inventory levels, defect levels, productivity, production waste, production costs | Operational performance of the firms was found to be positively related to lean implementation |
| Zarinah et al. 2017 | Hierarchical Regression Analysis | 44 malaysian firms | Pull system, quick setup,, quality at the source, total productive maintenance | quality, inventory minimization, delivery, productivity and cost reduction. | Lean production gives positive relationship in term of quality, inventory minimization, delivery, productivity and cost reduction |

| | | | | | |
|---|---|---|---|---|---|
| Iranmanesh et al 2019 | Partial least squares | 187 manufacturing firms in Malaysia | Process and equipment, manufacturing planning and control, human resources,<br>product design, supplier relationship, and customer relationship | | Our findings suggest that process and equipment, product design, supplier relationships,<br>and customer relationships have a positive and significant effect on sustainable performance. |
| Shafiq et al 2017 | Structural Equation modelling | 210 textıle firms ın Pakıstan | Process, people | | this study provided support for the positive and significant causal effect of TQM implementation on organisational performance. |
| Filho et al. 2016 | Partial least squares–Structural Equation modelling (SEM) | 64 companies of the Brazilian automotive supply chain | Standardised work, TPM, Problem-solving, Pull production, Set up reduction, production levelling | Lead time, Inventory, Quality On-time, Turnover | Brazilian companies are experiencing reduction of Lead time due to the implementation of TPM and reducing inventory based on the adoption of just-in-time practices |

## Appendix 2: Coding Form

The coding form for the meta-analytical review of the relationship between ILM practices and operational performance is given below;

1. Study Identification

a) Study ID: …………………………………………………………………….

b) Author(s): ………………………….......................................................

c) Year of Publication: ……………………………………………………….

d) Journal: ……………………………………………………………………….

e) Region Conducted: …………………………………………….…

2. Sample Characteristics

a) Sample Size (N): ………………………………………………………...

b) Size of the firm: ………………………………………………….

c) Type of the economy: ……………………………………………….

d) Type of industry: ……………………………………………………

3. Outcome Characteristics

a) Data Analysis Technique(s): …………………………………………………

b.

| Effect Size Calculation | | | |
|---|---|---|---|
| ILM Practices: | LM reliability | FP reliability | Effects sizes |
| | | | |
| | | | |
| | | | |
| | | | |
| Firm Perfomance | | | |
| | | | |
| | | | |
| | | | |
| | | | |

The coding process is guided by the following instructions in the table (app. 3)

**Appendix 3: Coding Instructions**

| | |
|---|---|
| | Study Identification |
| Study ID | Assign a unique identifier to the study |
| Author(s) | Record the last name(s) of the authors |
| Year | Record the year the study was published |
| Journal | Record the journal in which the study was published. |
| Country (Economy) | Record the country/region where the study was conducted |
| | Sample Characteristics |
| Sample Size | Record the sample size (N) of the study |
| Sector | Record the industry type of the sample |
| Industry | Record the business sector the sample works |
| Firm size | Record the firm size of the sample |
| | Outcome Characteristics |
| Method | Record the statistical method used to analyse study data |
| ILM Practices | Record the ILM constructs identified in the study with their effect sizes |
| Operational performance | Record the operational performance constructs measured in the study with the reliability. |

## Appendix 4: Screenshots of the results returned by the software

i) Aggregate Internal Lean Manufacturing and Operational Performance

# Meta-Analysis

Random-Effects Model (k = 30)

| | Estimate | se | Z | p | CI Lower Bound | CI Upper Bound |
|---|---|---|---|---|---|---|
| Intercept | 0.637 | 0.0392 | 16.2 | < .001 | 0.560 | 0.714 |
| | . | . | . | . | . | . |

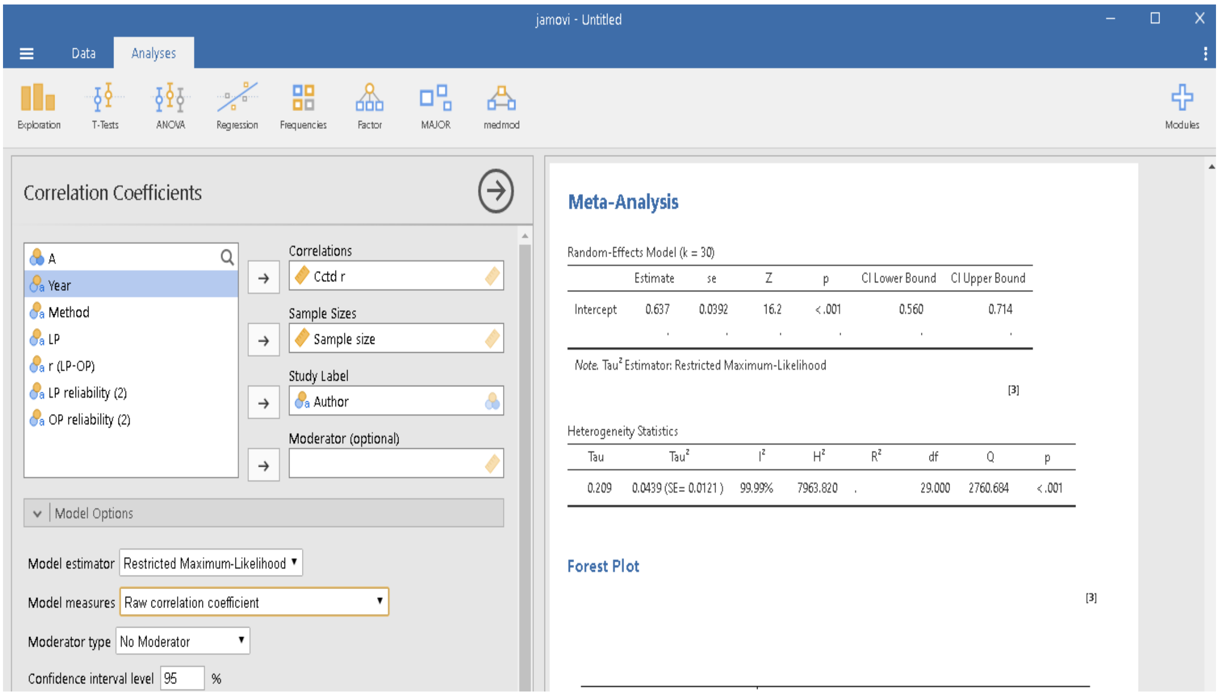
*Note.* Tau² Estimator: Restricted Maximum-Likelihood

[3]

Heterogeneity Statistics

| Tau | Tau² | I² | H² | R² | df | Q | p |
|---|---|---|---|---|---|---|---|
| 0.209 | 0.0439 (SE= 0.0121 ) | 99.99% | 7963.820 | . | 29.000 | 2760.684 | < .001 |

Screenshot of the Jamovi software computations for Agg ILMP and OP




Some of the screenshot of the excel spreadsheet coding and computations of ILMP-OP coding sample edit (Oto) - Excel (Ürün Etkinleştirilemedi)

Dosya Giriş Ekle Sayfa Düzeni Formüller Veri Gözden Geçir Görünüm Ne yapmak istediğinizi söyleyin... Oturum A

L22 =J22*J22*D22

| | A | B | C | D | E | F | G | H | I | J | K | L | M | N | O |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | | Article | year | N | Statistical method | Lean Practices | r(LP-OP) | LP reliability | OP reliability | A factor | cctd r | Study wt | cctd r wt | Pop r | Industry size |
| 2 | 1 | Panwar et al | 2017 | 121 | PLS | Aggregate Lean Practices | 0.844 | 0.771 | 0.750 | 0.760 | 1.110 | 69.968 | 77.658 | 0.616 | SME,LE |
| 3 | | | | | | | | | | | | | | | |
| 4 | 2 | Khanchanapon | 2014 | 186 | SEM/Bivariate | ALP | 0.183 | 0.84 | 0.800 | 0.820 | 0.223 | 124.992 | 27.903 | | SME .LE |
| 5 | | | | | | | | | | | | | | | |
| 6 | 3 | Rahman et al. | 2010 | 187 | Multiple regression | Aggregate lean practices | 0.572 | 0.794 | 0.759 | 0.776 | 0.737 | 112.695 | 83.036 | | LE, SME |
| 7 | | | | | | | | | | | | | | | |
| 8 | 4 | Valente et al. 2 | 2020 | 329 | PLS-SEM | ALP | 0.640 | 0.888 | 0.798 | 0.842 | 0.760 | 233.137 | 177.249 | | SME |
| 9 | | | | | | | | | | | | | | | |
| 10 | 5 | Marodin et al. 2 | 2017 | 64 | Regression | ALP | 0.441 | 0.826 | 0.783 | 0.804 | 0.548 | 41.393 | 22.698 | | SME,LE |
| 11 | | | | | | | | | | | | | | | |
| 12 | 6 | Chavez et al 20 | 2013 | 228 | Correlation | ALP (Pull, Set up, Qlty imp) | 0.253 | 0.721 | 0.761 | 0.741 | 0.342 | 125.099 | 42.728 | | SME,LE |
| 13 | | | | | | | | | | | | | | | |
| 14 | 7 | Negrão et al. 20 | 2019 | 217 | PLS-SEM | ALP | 0.554 | 0.894 | 0.904 | 0.899 | 0.616 | 175.374 | 108.074 | | SME, LE |
| 15 | | | | | | | | | | | | | | | |
| 16 | 8 | (Onofrei et al 2 | 2019 | 528 | regression analysis | ALP | 0.475 | 0.900 | 0.868 | 0.884 | 0.537 | 412.474 | 221.671 | | SME,LE |
| 17 | | | | | | | | | | | | | | | |
| 18 | 9 | Al-Zu'bi et al 20 | 2015 | 157 | regression | ALP | 0.523 | 0.707 | 0.709 | 0.708 | 0.739 | 78.698 | 58.135 | | SME,LE |
| 19 | | | | | | | | | | | | | | | |
| 20 | 10 | NAWANIR et al | 2010 | 139 | Multiple reg, correl. | ALP | 0.562 | 0.866 | 0.783 | 0.823 | 0.682 | 94.253 | 64.327 | | LE |
| 21 | | | | | | | | | | | | | | | |
| 22 | 11 | Chi Phan et al 2 | 2019 | 280 | Regression | ALP | 0.376 | 0.826 | 0.85 | 0.838 | 0.449 | 196.588 | 88.216 | | ME,LE |
| 23 | | | | | | | | | | | | | | | |
| 24 | 12 | Wickramasingh | 2016 | 30 | Correlations | ATPM | 0.640 | 0.755 | 0.765 | 0.760 | 0.842 | 17.327 | 14.592 | | |
| 26 | 13 | Chavez et al. 20 | 2014 | 228 | Correlations | ILP (Set up & Pull pdtn) | 0.349 | 0.721 | 0.801 | 0.760 | 0.459 | 131.675 | 60.471 | | SME,LE |
| 27 | | | | | | | | | | | | | | | |
| 28 | 14 | sahoo 2019 | 2019 | 148 | correlations | ALP | 0.668 | 0.888 | 0.8656 | 0.877 | 0.762 | 113.761 | 86.677 | | LE |
| 29 | | | | | | | | | | | | | | | |
| 30 | 15 | Sezen et al. 201 | 2011 | 207 | correlations | ALP | 0.501 | 0.92 | 0.82 | 0.869 | 0.577 | 156.161 | 90.076 | | SME,LE |
| 31 | | | | | | | | | | | | | | | |
| 32 | 16 | Alsmadi et al 2 | 2012 | 148 | | ALP | 0.802 | 0.822 | 0.908 | 0.864 | 0.928 | 110.464 | 102.545 | | SME,LE |
| 33 | | | | | | | | | | | | | | | |
| 34 | 17 | Marodin et al. 2 | 2017 | 64 | | ALP | 0.386 | 0.711 | 0.783 | 0.746 | 0.517 | 35.630 | 18.432 | | SME,LE |
| 35 | | | | | | | | | | | | | | | |
| 36 | 18 | (G.L.D. Wickran | 2017 | 1189 | Hierach. regression | ALP | 0.582 | 0.86 | 0.90 | 0.880 | 0.662 | 920.286 | 608.801 | | |
| 37 | | | | | | | | | | | | | | | |
| 38 | 19 | Sahoo & Yadav | 2017 | 121 | Multiple regression | ALP | 0.49 | 0.731 | 0.725 | 0.728 | 0.673 | 64.127 | 43.163 | | SME, LE |
| 39 | | | | | | | | | | | | | | | |
| 40 | 20 | Costa et al 2020 | 2020 | 145 | SEM | ALP | 0.678 | 0.86 | 0.900 | 0.880 | 0.771 | 112.230 | 86.490 | | SME,LE |
| 41 | | | | | | | | | | | | | | | |
| 42 | 21 | Saini & singh 20 | 2019 | 183 | Multiple regression | ALP | 0.862 | 0.972 | 0.953 | 0.962 | 0.896 | 169.516 | 151.823 | | SME,LE |
| 43 | | | | | | | | | | | | | | | |
| 44 | 22 | Nawanir et al | 2013 | 139 | Multiple regression | ALP | 0.495 | 0.69 | 0.608 | 0.648 | 0.764 | 58.313 | 44.565 | | LE |
| 45 | | | | | | | | | | | | | | | |
| 46 | 23 | Yadav et al 201 | 2019 | 425 | SEM | ALP | 0.897 | 0.835 | 0.775 | 0.804 | 1.115 | 275.028 | 306.673 | | SME |
| 47 | | | | | | | | | | | | | | | |
| 48 | 24 | Zarinah et al. 20 | 2017 | 44 | Regression | ALP | 0.719 | 0.944 | 0.938 | 0.941 | 0.764 | 38.961 | 29.769 | | SME |
| 50 | 25 | Iranmanesh et | 2019 | 187 | PLS | ALP | 0.310 | 0.826 | 0.884 | 0.855 | 0.363 | 136.544 | 49.536 | | LE |
| 51 | | | | | | | | | | | | | | | |
| 52 | 26 | Shafiq et al 201 | 2018 | 210 | SEM | ALP | 0.505 | 0.859 | 0.848 | 0.853 | 0.592 | 152.971 | 90.512 | | |
| 53 | | | | | | | | | | | | | | | |
| 54 | 27 | Vijay R. Kannar | 2015 | 556 | SEM | ALP | 0.085 | 0.866 | 0.719 | 0.789 | 0.108 | 346.196 | 37.292 | | SME, LE |
| 55 | | | | | | | | | | | | | | | |
| 56 | 28 | Belekoukias et | 2014 | 140 | Linear regression | ALP | 0.538 | 0.826 | 0.783 | 0.804 | 0.669 | 90.546 | 60.573 | | SME, LE |
| 57 | | | | | | | | | | | | | | | |
| 58 | 29 | Juan A. Marin-( | 2014 | 101 | PLS-SEM | ALP | 0.344 | 0.826 | 0.783 | 0.804 | 0.428 | 65.323 | 27.942 | | |
| 59 | | | | | | | | | | | | | | | |
| 60 | 30 | Shashi et al 201 | 2019 | 374 | SEM | ALP | 0.454 | 0.826 | 0.783 | 0.804 | 0.565 | 241.887 | 136.552 | | SME |
| 61 | | | | | | | | 19.815 | 20.392 | | | | | | |
| 62 | | | | 7075 | | | | | | | | | | | |
| 63 | | | | | | | | 0.826 | 0.816 | | | 4901.616 | 3018.179 | | |

# CURRICULUM VITAE

Ashiraf Kategaya is a Ugandan national who has studied from Uganda, Turkey and Portugal. His interests are in the domains of Industrial engineering, production and operations management.

He accumulated four years of work experience starting from the lower level as a machine maintenance trainee, machine workshop intern to assistant production supervisor to production manager in the manufacturing firms of Uganda from 2014-2017 until he left to further his studies in the field of Production management at Sakarya University, The Republic of Turkey.