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Development of a Lean Maturity Assessment Model Using Interval-Valued Spherical Fuzzy AHP Method

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Abstract

Continuously adding value to a company's products and services is inevitable in adapting to this evolving and challenging global market. That is why lean philosophy is becoming increasingly important and popular among companies, and they are relying more and more on it. It not only assists in increasing profitability and quality by eliminating all processes that provide no value to the customer but also enables increased flexibility in production and productivity. In this study, the criteria affecting the Lean Maturity Level (LML) were determined, and a lean maturity measurement model, which helps companies define and understand the level of lean maturity and lean effectiveness, was developed. A recently completed case study included data from an online survey with 116 questions, which were conducted on 187 middle to senior-level professionals in Türkiye from different industries. In this model, 9 main and 14 sub-lean criteria were generated to determine LML , and each criterion was weighted based on the assessments of experts. In this paper, the interval-valued spherical fuzzy AHP method is applied for the very first time to the weighting of the criteria of a lean maturity assessment model. After collecting data through an online survey study, Confirmatory Factor Analysis (CFA) in the IBM SPSS AMOS V26 program was applied to test the model fit, validity, and reliability. To determine the LMLs, the leveling scale (understanding, implementation, improvement, and sustainability) was used from the model for LMLs in manufacturing cells. As a result of the analysis of the survey results obtained from the participating companies, the overall LML was calculated as 2.55 out of 4. This result corresponds to the level 3 - improvement range on the leveling scale. The lean maturity success rate of surveyed companies was set at 64%.

Keywords: Lean manufacturing, Lean maturity assessment model, Interval-valued spherical fuzzy analytic hierarchy process, Confirmatory factor analysis.

1 | Introduction

In today's world, companies and other organizations always aim to perform better to survive and become more competitive. This goal leads them to seek more efficient production and management systems in the constantly changing conditions and today's competitive environment. To help companies achieve these goals, a series of tools, methodologies, and models are offered designed to improve organizations and achieve higher

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business performance. The Lean Management approach seems to be the most effective in terms of achieving significant productivity improvement in a relatively fast manner [1], considering that lean thinking and lean concepts are of great importance in a constantly evolving global market where information technologies are at the forefront. The main goal of lean thinking is to eliminate waste and continuously create more value for resources and processes. In today's competitive environment, companies must address the concepts of lean maturity in detail to make themselves stand out and assure continuity by increasing the level of lean maturity. They can only extend their quality and life cycle in these competitive conditions by measuring their performance through the methods they determine their Lean Maturity Levels (LMLs). In addition, an increase in quality levels, process and production improvement, customer satisfaction, and inventory control were the most frequently expressed benefits of the introduction of Lean Production [2]. Therefore, it is evident that the importance of finding a way to ensure a reliable and sustainable implementation of Lean is on the rise. However, implementation is not a simple process. According to the research of these authors, even before the 90s, there were some concerns about "how" to implement Lean practices. As also stated by Wan and Chen [3], the primary demand to provide information is 'how to become Lean'. Hence, the need to find a way to ensure that Lean implementations are practical and efficient at the same time is clear.

Lean Maturity Assessment Models (LMAM) are developed to define and track the lean journey of the enterprises easily. LMLs indicate the degree to which an organization is following lean practices [4], [5]. With an accurate and reliable implementation, based on the results, strengths and weaknesses in lean practices can be identified, the organization's lean progress can be observed, and actions can be defined to achieve the objectives. Thus, companies have well-defined roadmaps to move to the next level of lean maturity. As the uncertainties are eliminated, positive improvements in outputs such as lower complexity level, higher profitability, shorter delivery time, or higher consumer satisfaction rate can be more easily observed.

This study is based on a Maturity Model (MM), which consists of a self-assessment tool for defining the LML, the production areas, and warehouses. In this study, the primary criteria affecting the LML were determined in a broad scope, and then questions were formed under each criterion by feeding on the literature. After that, methods of measuring the LML were investigated. Based on the knowledge gap in this field, the purpose of this research is to help the following statements through the development of a dynamic, multi-dimensional Lean Maturity Model (LMM) tailored for management and operational level:

I. A company can assess its overall leanness through using the LMAM.

II. A company can easily define improvement points according to its LML.

III. A company can set the target for the next level of lean maturity.

IV. A company can have other outcome variables that are positively influenced by lean implementations.

Such as complexity level, profitability (in%), delivery time, consumer satisfaction rate, organizational performance, agility, and sustainability. Using this tool would be beneficial to managers, lean practitioners, and engineers in many ways, primarily in understanding current gaps in Lean adoption and in identifying further transformation opportunities. Since there is no one-best-way recipe for lean implementation [6], this study only intends to guide the firms with a detailed inspection opportunity of LML for mainly production and logistic areas.

2 | Literature Review

2.1 | Lean History

In 1978, Ohno published "Toyota Production System" (TPS) in Japan and credited Ford Production System and American supermarkets behind his Just-In-Time (JIT) thinking [7]. TPS is targeted at removing any waste and inconsistency in the production system. TPS consists of two pillars that are JIT and Jidoka [8]. At the start, because of its concept of reducing inventory and tangible benefits, few researchers [9] focused only on JIT. The success of TPS resulted in its wide acceptance by the manufacturing industries globally; later on, it was disseminated into other non-conventional industries, and the TPS philosophy only preceded the foundation of the more widely recognized term of 'Lean Production' (LP) [10]. The concept of LP was formally introduced in the paper 'triumph of the lean production system' by Krafcik in 1988 [11]. In 1990, the book the machine that changed the world was published by Womack and Jones [12], and the term LP gained more popularity. LP addresses the elimination of waste and makes the process flow more streamlined and efficient [13]. Today, in this current era of global competitiveness, lean principles have been applied in all sectors of manufacturing, banking, healthcare, and even non-profit organizations [14].

2.2 | Maturity Models

Based on the assumption of predictable patterns of evolution and change, MMs usually include a sequence of levels or stages that together form an anticipated, desired, or logical path from an initial state to maturity [15]–[18]. In this context, Maturity Levels (MLs) indicate an organization's current or targeted capabilities concerning a particular type of asset [19]. MMs are commonly applied to assess the as-is situation, to derive and prioritize improvement measures, and to control progress [20]. As for their application in practice, MMs are expected to disclose current and desirable MLs and to include respective improvement measures [15]. The intention is to diagnose and eliminate deficient capabilities. MMs are such tools as engines for continuously improving systems, roadmaps for guiding organizations, and blueprints for designing new entities [21]. On the other hand, in the development of any world-class manufacturing principles, performing an assessment is critical for the successful implementation process [22]. The organization needs a well-defined MM along with an evaluation that consists of multiple checklists to monitor the level of lean maturity over time and evaluate the progress of the process throughout the lean journey. Lean implementation is also a gradual process to shape the organizational culture. Therefore, the maturity assessment models need to be implemented gradually and step-by-step, following the evolution of lean change, to achieve the next level of lean status [23]. According to the literature review of the LML tools by Cetnarski et. al. [24], between the years 1996 and 2015, 51 models have been evaluated. It is undoubtedly an indication that there is an increasing academic interest in MMs [25]. In this study, the leveling scale in the model for LML in MC, which was developed by Maasouman and Demirli [14], has been used to determine the LML of the organization. LML used in this study is given in *Table 1*. *Table 2* was created to show the most recent lean MM, which is mentioned in the relevant articles, and maintained to collect different models with their different levels of lean maturity.

Table 1. Four levels of LMM in production cells.

Focus of the Level	Expected Level of Perception /Implementation	Expected Level of Results	Description
Capability of the people	Understanding (training, standardization, not applicable/lack of implementation)	Quantitative progression of standardization	Quantitative progress in deploying the tools/concepts to raise awareness of the issue
		Qualitative Progression of standardization	Qualitative progress in deploying the tools/concepts to deepen understanding of the issue
Results and performance	Implementation	Effectiveness	Deployment of tools/concepts in a way that is conducive to the achievement of expected results.
	Improvement	Efficiency	Deployment tools/concepts in a way that achieves the expected results and simultaneously uses resources efficiently.
Autonomy and flexibility	Sustainability	Daily excellence	Deployment tools/concepts and improve results continuously and autonomously

3 | Methodology

This study aims to offer a standardized LMM that is developed using the very first-time Interval-Valued Spherical Fuzzy Analytic Hierarchy Process (IVSF-AHP) as a decision-making method and validated by using Confirmatory Factor Analysis (CFA). Also, the proposed model that meets the requirements of production areas and warehouses aims to help managers, lean practitioners, and engineers in the sector significantly. Therefore, a conceptual model is developed based on the review of the literature.

Firstly, extensive research is conducted not only in the area of lean concepts, principles, tools, and objectives but also in MMs. In the design phase, LMLs and criteria are defined. In this model, 9 main 14 sub-lean criteria (management and leadership, quality, JIT, lean methods (gemba-kaizen, ergonomics and 5S, VSD, waste), facility management TPM and OEE, supply chain management, production processes, working conditions, people) were used. There are many more lean criteria and tools in the literature. *Table A3* shows a detailed list of criteria considered under different studies. All the criteria used in the study can be shown in appendix *Table A4* with their codes and literature references. It is apparent that to assess the ML accurately, a broader perspective is required. Hence, when determining the criteria under lean production, human-oriented criteria such as management factors, working conditions, and people are among the factors that define the LML. The leveling scale in the model for LML in MC is used as a leveling scale. As a second task of the design phase, the design of the lean maturity checklists and finalization of the survey instrument are completed. The group of experts, who consisted of 5 people, supported this study with their know-how and experiences in the LP field. They provided data for the criteria weightings and pre-testing of the assessment model. Each criterion is weighted based on the assessments of experts and IVSF-AHP calculations in the EXCEL to define their degree of importance.

Then, several modifications and refinements are done to get the best and final version of the LMAM using IVSF-AHP. After collecting data through a survey study, CFA in the IBM SPSS AMOS V26 program was applied to test the model fit, validity, and reliability. Several iterations are completed to reach an adequate model with good model fit, validity, and reliability. *Fig. A1* shows the overall framework of the research methodology in the appendix section.

3.1 | Measurement Phase

Interval-values spherical fuzzy AHP

Kutlu Gündogdu and Kahraman [26] have recently introduced the Spherical Fuzzy Sets (SFS). These sets are based on the fact that the hesitancy of a decision-maker can be defined independently from membership and non-membership degrees, satisfying the following conditions:

$$0 \leq \mu_{\tilde{A}}^2(u) + v_{\tilde{A}}^2(u) + \pi_{\tilde{A}}^2(u) \leq 1, \text{for all } u \in U, \tag{1}$$

where μAu, vAu, and πAu are the degrees of membership, non-membership, and hesitancy of u to ~A for each u, respectively. On the surface of the sphere, *Eq. (1)* becomes

$$\mu_{\tilde{A}}^2(u) + v_{\tilde{A}}^2(u) + \pi_{\tilde{A}}^2(u) = 1, \text{for all } u \in U. \tag{2}$$

The idea behind SFS is to let decision-makers generalize other extensions of fuzzy sets by defining a membership function on a spherical surface and independently assigning the parameters of that membership function with a larger domain. SFS is a synthesis of PFS and NS. The proposed IVSF-AHP method consists of several steps, as given in this section.

Step 1. Form the hierarchical structure based on four levels. In this step, a hierarchical structure consisting of at least three levels is developed. Level 1 shows an objective that means selecting the best alternative based on the score index. The scoring index is estimated based on a finite set of criteria C ={C1, C2, . . . , Cn}, which are shown at Level 2. Many sub-criteria are at Level 3 defined for any criterion C in this hierarchical structure. Therefore, at Level 4, a discrete set of m feasible alternatives X={x1, x2, . . . , xm} (m ≥ 2) is defined, and also, there is a discrete set of K feasible decision-makers for each level [27].

Step 2. Construct pairwise comparison matrices. Pairwise comparisons using interval-valued spherical fuzzy evaluation matrices are constructed based on linguistic terms of importance. The CR of each pairwise comparison matrix is calculated. For this purpose, switch the linguistic terms in the pairwise comparison matrix to their corresponding score indices given in *Table A1* in the Appendix. Then, apply the classical consistency check ratio formula [28]. It can be said that pairwise comparison matrices are consistent when the CR is less than 10%. Otherwise, decision-makers must consider their judgments once again.

Step 3. Aggregate the individual evaluator groups' interval-valued spherical fuzzy weights. In real-life problems, there can be many different types of evaluators. Firstly, to get individual evaluator groups' weights ($\tilde{\omega}_j^{S_k}$), each criterion and alternative pairwise comparison matrices taken from different types of evaluators are aggregated by using the IVSWAM operator.

Step 4. Constitute the interval-valued spherical fuzzy local weights of each criterion. Then, to obtain the interval-valued spherical fuzzy local weights ($\tilde{\omega}_j^{S}$), $\tilde{\omega}_j^{S_k}$ values formed according to the evaluations of different types of evaluators are aggregated with the help of an Interval-Valued Spherical Weighted Geometric Mean (IVSWGM).

Step 5. Construct the hierarchical form to obtain global weights. *Eq. (3)* de-fuzzified the criteria weights by using a modified score function. 1.0 is added to the previous definition of score function since a positive score value may be more beneficial for spherical calculations.

$$\text{Defuzz }(\tilde{\omega}_j^{S}) = \tilde{\omega}_j^{\text{lokal}} = \frac{(\mu^-)^2+(\mu^+)^2-(v^-)^2-(v^+)^2-(I^-/2)^2-(I^+/2)^2}{2}+1. \quad (3)$$

Step 6. The local weights at each level are multiplied by each related sub-criterion local weight to estimate the final global weights ($\overline{\omega}_j^{\text{global}}$)for each criterion and sub-criterion. After necessary multiplication, *Eq. (4)* can be used to normalize the global criteria weights.

$$\overline{\omega}_j^{\text{final}} = \frac{\overline{\omega}_j^{\text{global}}}{\sum_{j=1}^{n} \overline{\omega}_j^{\text{global}}}. \quad (4)$$

After this calculation, normalized global weights of each criterion and sub-criterion are obtained. If alternatives exist in the problem, the algorithm must continue with Step 7.

Step 7. Compute the weighted decision matrix and find the global preference weights ($\tilde{s}_{S_{ij}}$) in terms of alternatives. The normalized global criteria weights ($\overline{\omega}_j^{\text{final}}$) are multiplied by the decision matrix utilizing *Eq. (5)*.

$$\tilde{s}_{S_{ij}} = \overline{\omega}_j^{S}.\, \tilde{s}_{S_i}. \quad (5)$$

Step 8. Defuzzify the final score of each alternative and normalize the de-fuzzified values.

Step 9. Determine the rank among alternatives with respect to the normalized and defuzzified final scores. The best alternative has the largest final score value.

Table 2. Literature review on determining lean maturity levels.

Model	Author	Maturity Levels						
		0	1	2	3	4	5	6
Jorgensen	[51]		Sporadic production optimization	Basic lean understanding and implementation	Strategic lean interventions	Proactive lean culture	Lean in the extended manufacturing enterprise	
LCMM	[52]	Uncertain	Awakening	Systematic	Integrated	Challenging		
BPI	[53]	The Lean approach is not described or poorly described	The Lean approach is described but not structured with a procedure model	The Lean approach is structured with a procedure model	The Lean approach is structured with a procedure model, and one or more techniques are described for some or all the activities of the procedure model	The Lean approach is structured with a procedure model, with techniques and the results of some of the activities or all the activities described	The Lean approach is structured as in level 4, but for each activity, the roles are defined	The Lean approach is structured as in level 5, but an information model is also provided
Lesat Lai	[54]		Some awareness	General Awareness	A systematic approach/methodology deployed in varying stages across most areas	Continuous improvement across the enterprise	Exceptional, well-defined, innovative approach is fully deployed across the extended enterprise.	
Model for lean maturity level in MC	[14]		Understanding (training, standardization)	Implementation	Improvement	Sustainability		
IDEAL	[55]		Initial	Defined	Enhanced	Advanced integrated	Long-term optimized	
Lean manufacturing maturity model	[50]		Inconsistent and unstable results	Department-level management, local efficiency improvement	Well-defined company-wide processes, standardization, and best practices	Continuous improvement	Optimized	
A conceptual model for LM maturity level	[56]		Understanding	Implementation	Success			

3.2 | Analysis and Verification Phase

Scale development and validation: CFA

The process of theory building relies on the existence of solid proof based on a rigorous research methodology so that researchers can develop reliable, valid, and realistic diagnostic instruments [29]. Professionals can successfully use such tools for the development and advancement of any theory, including the definition of LML. Questionnaire surveys are widely acknowledged as a method of measuring the perceptions of various groups of experts and practitioners on a particular topic. CFA is a type of Structural Equation Modeling (SEM) that deals specifically with measurement models, that is, the relationships between observed measures or in dicators (e.g., test items, test scores, behavioral observation ratings) and latent variables or factors [30]. CFA requires that it should be based on logic and/or theory, and hence, the researcher should have a good knowledge of the latent factors that explain the variation in the observed variables [31]. The adequacy of the CFA model is based on acceptable measures of model fit, reliability, and construct validity for scales [32]. Since there are multiple benefits of the CFA approach, in this study, CFA is used to perform factor analysis in defining lean maturity measurement models and their associated latent factors and observed variables.

Model fit

In the literature, there are several statistical methods to measure the model fit in CFA, such as $\chi 2$, Incremental Fit Indices, Absolute Fit Indices, and many more. All aim to evaluate different facets of a model fit.

The Chi-Square value is the traditional measure for evaluating overall model fit and 'assesses the magnitude of discrepancy between the sample and fitted covariances matrices' [33]. Incremental fit indices, also known as comparative [34] or relative fit indices [35], are a group of indices that do not use the chi-square in its raw form but compare the chi-square value to a baseline model. An incremental fit index is used to assess the improvement in fit between default and baseline models. A null model in which no items covary is the most generally used baseline model [31]. Commonly used incremental fit indexes include, among other things, the Normed Fit Index (NFI), the Tucker–Lewis Index (TLI), the Relative Noncentrality Index (RNI), and the Comparative Fit Index (CFI) [33]. Absolute fit indices determine how well a priori model fits the sample data [35]. There is no reference model used in this index; however, an implicit or explicit comparison is made to a saturated model that reflects a perfectly fitting model [32]. The absolute fit index category includes the Chi-Square test, RMSEA, Goodness-of-Fit Index (GFI), Adjusted Goodness-of-Fit Index (AGFI), RMR, and SRMR. To check whether the CFA model is adequate, there are multiple theories and philosophies concerning how many indices/statistics should be reported and what combinations of these indices are appropriate. Some of these statistics/indices are influenced by sample sizes or the ratio of indicators per factor and may not provide an adequate representation of the model fit [36]. For instance, the Chi-Square statistic is theoretically expected to be non-significant ($p > 0.05$) for a good model fit. However, studies have shown that the Chi-Square Statistic is very sensitive to sample size. For a large sample size that is typically required for CFA and SEM models, the Chi-Square statistic and its associated probability value will invariably turn out to be significant ($p < 0.05$). Therefore, it was suggested to use the Chi-Square/df measure, which is required to fall between 1 and 3 for an acceptable fit. Similarly, GFI, which is a measure of absolute fit, is also largely influenced by sample size. Some of these indices work better in certain scenarios, while others perform well in other scenarios [32]. To address these problems, researchers have suggested the use of multiple fit indices to provide a more holistic view of Goodness of Fit, addressing issues related to sample size and model complexity [37]–[39]. Given such varied suggestions on the use of the right set of Indices, researchers have suggested specific key indices that must be reported in research findings [33], [36], [40], [41]. In light of the aforementioned explanations on the indices, *Table 3* shows that the following required set of indices and cutoff criteria will be evaluated in this study.

Characteristic of good measurement–validity and reliability

The characteristics of a suitable measurement instrument should address the ability of the tool to measure what it intends to measure [42] adequately. Scale reliability and validity are the two primary criteria that are used to ensure whether the measurement instrument is good enough to do the measurement. Without ensuring reliability and validity, measurement scales cannot be standardized and will not be able to measure the required construct [29].

Table 3. Set of indices and cutoff criteria.

Model Fit	The Goodness of Fit Measure	Acceptable Range	Required Indices and Cutoff Criteria
Incremental fit	NFI	0 to 1	No
	TLI	0 to 1	No
	Relative non-centrality index	0 to 1	No
	CFI	>0.95 – Excellent 0.9 to 0.95 - Good	Yes
Absolute fit	Chi-square/df	1 to 3	Yes
	Root mean square error of approximation	<0.06 – Excellent 0.06 to 0.08 – Good	Yes
	Standardized root mean square residual	<0.08 – Excellent 0.08 to 0.10 - Good	Yes
Classic goodness of fit	$\chi2$ goodness-of-fit statistic		No

The reliability of a scale is the ability of the scale to provide consistent results [43]. Even though reliability and validity are analytically distinguishable, they are related as reliability is a prerequisite to ensure validity [44]. Equivalent forms, split halves method, test–retest method, internal consistency method using Cronbach's alpha, and Composite Reliability (CR) can be given as examples as a few of many applications. In CFA, researchers have argued that CR is a better measure to ensure internal consistency [45]. Unfortunately, there is no consensus in the methodological literature on scale validity. Commonly used validity types include content, convergent, discriminant, and criterion-related validity [32]. Thestandardization of the instrument can be carried out by tests of unidimensionality, reliability, and construct validity (including content, convergent, discriminant, and criterion-related validities) using a CFA approach [32]. *Table 4* shows a set of reliability and validity measures, as well as their description and cutoff criteria, that are needed for CFA.

Table 4. Cutoff criteria for reliability and validity measures in CFA.

Purpose	Measure	Description	Acceptable Values
Reliability	CR	An indicator of the shared variance among the observed variables used as an indicator of a latent construct.	CR>0.7 CR>AVE
Content validity	Judgemental	The degree to which the content of these items adequately represents the universe of all relevant items under survey.	NA
Convergent validity	Average variance extracted	AVE refers to the amount of variance extracted by a latent factor as compared to its measurement error.	>0.5
Discriminant validity	Max. Shared Squared Variance Average	Maximum amount of squared variance shared by a latent factor with any other latent factor.	AVE>MSV
	shared squared variance	Average of all the squared variances of the latent factor and other latent factors.	AVE>ASV
Criterion validity	Concurrent	Typically, regression analysis of an output criterion with the latent factors is used to check for significance.	ρ<0.01 R^2 (above 80%)

4 | Implementation

4.1 | IVSF-AHP Implementation

The algorithmic steps of the IVSF-AHP method are as follows.

Step 1. The problem is defined. The criteria required for the decision and model itself are determined; these are management and leadership, quality, JIT, lean methods (gemba-kaizen, ergonomics, and 5S, VSD, waste), facility management TPM and OEE, supply chain management, production processes, working conditions, people and then the priorities criteria are defined. The importance ranking is prepared in line with the opinions of experts.

Step 2. A hierarchical structure is created. *Fig. 1* shows a hierarchical structure of evaluation of LMM. At the top is the main goal to be achieved. Below are the main criteria and sub-criteria. At the bottom of the hierarchy are the alternatives. The stage of the hierarchy number depends on the complexity of the problem and the degree of detail. When creating the hierarchy, the same options in the plane are considered to be completely independent of each other.

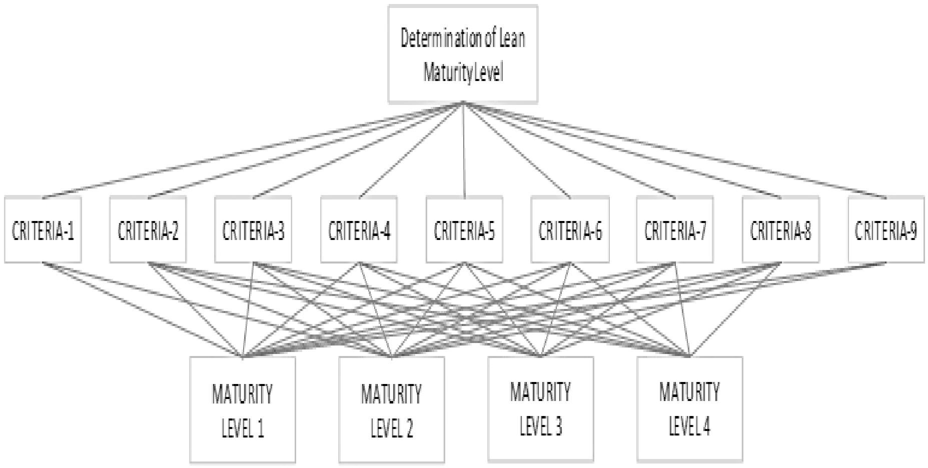

Fig. 1. Hierarchical structure of evaluation of LMM.

Step 3. A matrix of pairwise comparisons is created. Using a scale of 1 to 9, matrices are created comparing the decision options according to the criteria, first considering the main criteria, then the sub-criteria, if any, and finally all criteria. As described in *Eq. (6)*, comparison matrices are square matrices with diagonal elements of 1.

$$A = \begin{bmatrix} 1 & a_{12} & \cdot & \cdot & \cdot & a_{1n} \\ a_{21} = 1/a_{12} & 1 & \cdot & \cdot & \cdot & a_{2n} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ a_{n1} = 1/a_{1n} & a_{n2} = 1/a_{2n} & \cdot & \cdot & \cdot & 1 \end{bmatrix}. \tag{6}$$

α_{ij} is the pairwise comparison value of criterion i and criterion j and the value of α_{ji} is obtained from $1/\alpha_{ij}$. This is known as the correspondence function. α_{ij} value is the answer to the 'In which ratio should the criterion i be preferred over the criterion j?' question. Decision alternatives are compared separately according to each criterion. Decision matrices are created using the 1/9-9 comparison scale. The comparison scale with abbreviation code and score indices is shown above in *Table 3*. To calculate the weights of the criteria listed according to the degree of importance, pairwise comparisons were made between the criteria in the light of experts' views and knowledge *Table 5*.

Table 5. LMAM criteria pairwise comparison of Expert 5.

	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	EI	EI	HI	SMI	SMI	HI	SMI	SMI	EI
C2		EI	HI	EI	SMI	HI	EI	HI	SLI
C3			EI	LI	LI	EI	LI	SLI	LI
C4				EI	EI	HI	SLI	SMI	LI
C5					EI	SMI	LI	EI	LI
C6						EI	LI	EI	LI
C7							EI	VHI	EI
C8								EI	LI
C9									EI

Step 4. Normalize the Pairwise Comparison (PC) matrices. Each element in the matrix is normalized by dividing by the sum of its columns. The sum of each column of the normalized matrix equals 1. The calculation phases have been shown for expert 5 in *Table 6* and *Table 7*.

Table 6. LMAM normalization of PC – step 1.

	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	1.00	1.00	5.00	3.00	3.00	5.00	3.00	3.00	1.00
C2	1.00	1.00	5.00	1.00	3.00	5.00	1.00	5.00	0.33
C3	0.20	0.20	1.00	0.20	0.20	1.00	0.20	0.33	0.20
C4	0.33	1.00	5.00	1.00	1.00	5.00	0.33	3.00	0.20
C5	0.33	0.33	5.00	1.00	1.00	3.00	0.20	1.00	0.20
C6	0.20	0.20	1.00	0.20	0.33	1.00	0.20	1.00	0.20
C7	0.33	1.00	5.00	3.00	5.00	5.00	1.00	7.00	1.00
C8	0.33	0.20	3.00	0.33	1.00	1.00	0.14	1.00	0.20
C9	1.00	3.00	5.00	5.00	5.00	5.00	1.00	5.00	1.00
Total	4.73	7.93	35.00	14.73	19.53	31.00	7.08	26.33	4.33

Table 7. LMAM normalization of PC – step 2.

	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	0.211	0.126	0.143	0.204	0.154	0.161	0.424	0.114	0.231
C2	0.211	0.126	0.143	0.068	0.154	0.161	0.141	0.190	0.077
C3	0.042	0.025	0.029	0.014	0.010	0.032	0.028	0.013	0.046
C4	0.070	0.126	0.143	0.068	0.051	0.161	0.047	0.114	0.046
C5	0.070	0.042	0.143	0.068	0.051	0.097	0.028	0.038	0.046
C6	0.042	0.025	0.029	0.014	0.017	0.032	0.028	0.038	0.046
C7	0.070	0.126	0.143	0.204	0.256	0.161	0.141	0.266	0.231
C8	0.070	0.025	0.086	0.023	0.051	0.032	0.020	0.038	0.046
C9	0.211	0.378	0.143	0.339	0.256	0.161	0.141	0.190	0.231

Step 5. The priority vector is calculated. The sum of each row of the normalized matrix is divided by the dimension of the matrix and averaged. These values are the importance weights calculated for each criterion. These weights form the priority vector.

$$w_i = \left(\frac{1}{n}\right) \sum_{i=1}^{n} a'_{ij} \quad \text{, i, j= 1,2,.....,n.} \tag{7}$$

Eq. (7) is used. Thus, percentage importance distributions showing the importance values of the criteria relative to each other are obtained. *Table 8* shows the calculations.

Table 8. Calculations of priority vector.

Criteria % Weights (w)	D=A*w	ei=(A*w)/w
0.20	1.98	10.10
0.14	1.38	9.76
0.03	0.25	9.45
0.09	0.88	9.60
0.06	0.62	9.52
0.03	0.29	9.58
0.18	1.80	10.14
0.04	0.41	9.50
0.23	2.31	10.14
	Total	87.79

Step 6. CR is calculated. After pairwise comparisons and prioritization, the consistency of the comparison matrices is calculated.

To determine whether a matrix resulting from pairwise comparison judgment is consistent or not, it is necessary to calculate the coefficient called "Consistency Index (CI)," which is one of many methods. CI is calculated with *Eq. 8*.

$$CI = \frac{\lambda_{max} - n}{n - 1}. \tag{8}$$

$$\lambda_{max} = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{\sum_{j=1}^{n} a_{ij} w_j}{w_i} \right). \tag{9}$$

To evaluate consistency, the "Random Index (RI)" value should be known. RI values defined for n-dimensional comparison matrices are given in *Table 9*. After determining the CI and RI values, the CR is calculated. It has been shown in *Table 10*.

Table 9. RI values according to the size of comparison matrices.

n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.53	1.56	1.57	1.59

Table 10. Consistency ratio.

CI	CR	λmax	RI (Randomness index)
0.094	0.065	9.755	1.450

$$CR = CI/RI^*. \tag{10}$$

If the CR defined by *Eq. (10)* is less than 0.10, the comparison matrix is considered to be consistent. Steps 3-6 were repeated for each of the experts.

Step 7. A pairwise comparison matrix for the criteria is created, and the priority vector of the decision options is calculated. This priority vector can also be defined as a weight vector for the criteria. Comparisons of the criteria in the pairwise comparison matrix were made with the help of the IVSF-AHP method, which consists of 9 categories. These comparisons are based on the difference in the attractiveness of the criteria and the degree of impact of the criteria on lean maturity.

Step 8. Decision alternatives are ranked. Priority vectors obtained for the criteria are combined to create the complete priorities matrix. The resulting vector is obtained by multiplying and summing the complete priorities matrix and the priority vectors of the decision alternatives. The decision alternative with the highest weight in this vector is determined as the decision alternative that should be preferred for the solution of the problem. *Table 11* shows fuzzy weights, and *Table 12* illustrates the de-fuzzification of them.

Table 11. Fuzzy weights for each criterion.

	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	1.00	1.32	1.57	1.44	1.40	1.44	1.34	1.53	1.47
C2	0.76	1.00	1.27	1.04	1.09	1.01	0.73	1.15	1.12
C3	0.64	0.79	1.00	0.78	0.92	0.91	0.77	0.78	0.96
C4	0.69	0.96	1.29	1.00	0.97	1.15	0.78	1.19	1.14
C5	0.71	0.92	1.09	1.03	1.00	0.95	0.61	1.02	0.98
C6	0.69	0.99	1.10	0.87	1.05	1.00	0.76	1.20	1.12
C7	0.75	1.37	1.30	1.28	1.65	1.32	1.00	1.57	1.42
C8	0.65	0.87	1.29	0.84	0.98	0.83	0.64	1.00	0.96
C9	0.68	0.89	1.04	0.87	1.02	0.89	0.71	1.03	1.00
Total	6.6	9.1	10.9	9.1	10.1	9.5	7.3	10.5	10.2

Table 12. De-fuzzification and normalization of fuzzy weights.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	Priority Index	Rank
C1	0.15	0.14	0.14	0.16	0.14	0.15	0.18	0.15	0.14	0.151	1
C2	0.12	0.11	0.12	0.11	0.11	0.11	0.10	0.11	0.11	0.110	3
C3	0.10	0.09	0.09	0.08	0.09	0.10	0.10	0.07	0.09	0.091	9
C4	0.11	0.11	0.12	0.11	0.10	0.12	0.11	0.11	0.11	0.110	4
C5	0.11	0.10	0.10	0.11	0.10	0.10	0.08	0.10	0.10	0.100	6
C6	0.11	0.11	0.10	0.09	0.10	0.11	0.10	0.11	0.11	0.105	5
C7	0.11	0.15	0.12	0.14	0.16	0.14	0.14	0.15	0.14	0.139	2
C8	0.10	0.10	0.12	0.09	0.10	0.09	0.09	0.10	0.09	0.096	8
C9	0.10	0.10	0.09	0.10	0.10	0.09	0.10	0.10	0.10	0.098	7
Total	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.00	

4.2 | CFA Implementation

A total of 116 survey items were created for the empirical validation of the 9 main 14 sub-axes LMM. The questionnaire survey is based on a 5-point Likert scale, where 0 is strongly disagree or lack of implementation and 4 is strongly agree. This instrument was developed based on extensive research of lean literature (theoretical, conceptual, experimental, and practical). To ensure the content validity of the survey instrument and identify and calculate the accurate criteria weightings, a pilot study was conducted with a group of 5 experts (academics, researchers, lean engineers, managers, and practitioners). Several iterations of the tool were created based on comments and suggestions of experts and calculations of the IVSF-AHP method, and the final version was designed to maximize all aspects of Lean maturity as they relate to the 9 main 14 sub-axes. The results were gathered through a broad online survey of 26 medium and large-sized companies from different sectors, with responses from 187 respondents who are mostly lean engineers, lean managers, and practitioners. As a result of the analysis of the survey results obtained from the participating companies, the overall LML was calculated as 2.55 out of 4. This result corresponds to the Level 3 - Improvement range on the leveling scale from the Model for LML, which is used in the study. As an example of the practical use of the developed model for assessing the maturity of lean manufacturing, *Table 13* shows the average of the answers given by Company 1 to the questions under each criterion and the score obtained by multiplying these averages by the criterion weights.

Table 13. The practical use of the developed model.

Criteria	C1	C2.1	C2.2	C2.3	C3	C4.1	C4.2	C4.3	C4.4	C5	C6	C7	C8	C9
Company 1	2.333	2.222	2.167	2.400	1.889	2.333	2.182	2.000	2.111	1.818	1.889	2.000	2.167	2.200
Priority Index	0.151	0.110	0.110	0.110	0.091	0.110	0.110	0.110	0.110	0.100	0.105	0.139	0.096	0.098
Weighting	0.352	0.249	0.249	0.249	0.172	0.237	0.237	0.237	0.237	0.182	0.198	0.278	0.208	0.216
Overall Score	2.092													
Rate	52%													
LML	Level 3: improvement - efficiency													

Deployment tools and concepts in a way that achieves the expected results and simultaneously uses resources efficiently. The LML overall rate of surveyed companies was set at 64%. Moreover, all items on the survey instruments were randomized to prevent bias. An example of a checklist that is used for Lean maturity measurement of leanness indicators is presented in the Appendix in *Table A2*.

CFA–results and discussion

LMAM has been constructed upon the identified 9 main 14 Sub-criteria. In order to determine whether the goodness of the model fits well overall, the following hypothesis has been proposed: H0 Lean maturity measurement model is a multi-dimensional construct consisting of the previously mentioned 9 main 14 Sub-axes.

CFA analysis was conducted using IBM SPSS AMOS V26 software. A graphical display can be shown for LMM axes in *Fig. 3*. The results which are derived from CFA analysis are in *Table 14* and *Table 15*. The required model fit indices and cutoff criteria specify that all the indices remain in an acceptable range. *Table 14* shows strong evidence of model fit because all mandatory indices such as CFI, RMSEA, and SRMR belong to the results of the group "excellent," and also, Chi-square/df is in the acceptable range. The CR values shown in *Table 15* indicate that for all the axes of LMAM, they are either above the requirement of 0.7. These results display a strong CR of the criteria. The values of Average Variance Extracted (AVE) shown in *Table 15* are higher than the required value of 0.5, providing strong evidence of convergent validity. Measures of discriminant validity, like Maximum Shared Squared Variance (MSV) and Average Shared Squared Variance (ASV), also meet the necessary criteria to provide strong evidence of discriminant validity. The respondents were asked to rate the ML of their organization in percentage terms, and this outcome was used to test concurrent validity. *Table 15* shows the results of the regression analysis between the 14 sub-axes and ML. The results demonstrate the existence of strong concurrent validity, with a high R2 of 86.79%, confirming the statistical significance of the MM and the 14 axes individually. Given the strong evidence of model fit and the reliability and validity measures, it can be concluded that the hypothesis "H0 Lean maturity measurement model is a multi-dimensional construct consisting of the previously mentioned 9 main 14 Sub-axes." is acceptable.

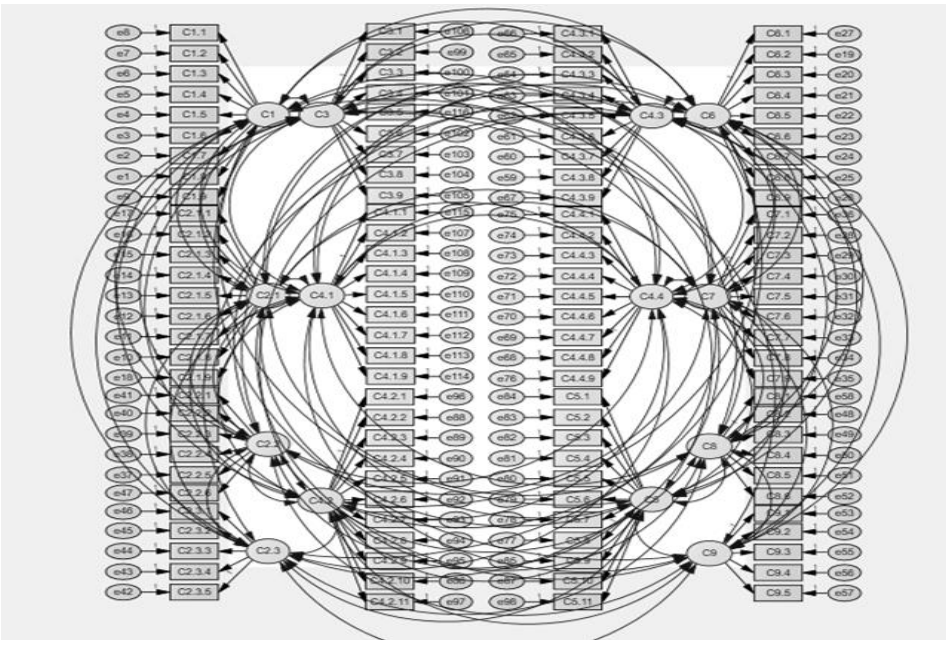

Fig. 2. A graphical display in IBM SPSS AMOS V26.

Table 14. Model fit results model.

Model fit	The goodness of fit measure	Acceptable range	Value	Review of results
Incremental fit	CFI	>0.95 – Excellent 0.9 to 0.95 - Good	0.985	Excellent
Absolute fit	Chi-square/df	1 to 3	1.719	Good
	Root mean square error of approximation	<0.06 – Excellent 0.06 to 0.08 - Good	0.040	Excellent
	Standardized root mean square residual	<0.08 – Excellent 0.08 to 0.10 - Good	0.059	Excellent

Table 15. Results of CFA–reliability and validity (convergent and discriminant).

#	Code	Criteria	AVE	CR	ASV	MSV	Criteria
1	C1	Management and leadership	0.568	0.896	0.024	0.051	
2	C2	Quality	0.594	0.828	0.015	0.114	
2.1	C2.1	Total quality management	0.635	0.811	0.033	0.064	
2.2	C2.2	Standardization and standard work	0.587	0.836	0.019	0.098	Reliability CR > 0.7 CR > AVE Convergent validity AVE > 0.5 Discriminant validity AVE > MSV AVE > ASV
2.3	C2.2	Jidoka	0.688	0.874	0.025	0.099	
3	C3	Just in time	0.576	0.792	0.043	0.105	
4	C4	Lean techniques	0.659	0.839	0.027	0.102	
4.1	C4.1	Gemba and kaizen	0.607	0.901	0.038	0.078	
4.2	C4.2	Ergonomy and 5S	0.572	0.873	0.046	0.057	
4.3	C4.3	Value stream mapping	0.678	0.914	0.032	0.124	
4.4	C4.4	Waste and loss management	0.602	0.875	0.030	0.120	
5	C5	Facility management	0.553	0.905	0.026	0.081	
6	C6	Supplier relations management	0.579	0.797	0.031	0.471	
7	C7	Production processes	0.551	0.858	0.044	0.063	
8	C8	Working conditions	0.624	0.926	0.041	0.117	
9	C9	People	0.545	0.867	0.034	0.089	

Table 16. Result of regression analysis between 1 axes and ML (concurrent validity).

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	14	2.33538	0.166813	370.05	0.000
Management and leadership	1	0.03259	0.032589	72.29	0.000
Quality					
Total quality management	1	0.01048	0.010480	23.25	0.000
Standardization and standard work	1	0.01766	0.017657	39.17	0.000
Jidoka	1	0.02018	0.020181	44.77	0.000
Just in time	1	0.01454	0.014535	32.24	0.000
Lean Techniques					
Gemba and Kaizen	1	0.02175	0.021748	48.24	0.000
Ergonomy and 5S	1	0.01783	0.017833	39.56	0.000
Value stream mapping	1	0.01561	0.015612	34.63	0.000
Waste and loss management	1	0.01472	0.014718	32.65	0.000
Facility Management	1	0.01328	0.013282	29.46	0.000
Supplier relations management	1	0.01164	0.011637	25.82	0.000
Production processes	1	0.01535	0.015353	34.06	0.000
Working conditions	1	0.02021	0.020209	44.83	0.000
People	1	0.02049	0.020494	45.46	0.000
Error	172	0.07753	0.000451	-	-
Total	186	2.41292	-	-	-
Model summary	S	R-Sq	R-Sq(adj)	R-Sq(pred)	
	0.0212317	86.79%	96.53%	96.24%	

5 | Conclusion

This research and the proposed MM aim to help industry managers, engineers, researchers, and practitioners evaluate the leanness of companies. The model and suggested methodology are a framework to understand

and develop lean philosophy progressively, especially in the production areas. In the light of generated knowledge, the model can be tweaked in detail by lean practitioners.

It has been used for the very first time in the IVSF-AHP method in a study of evaluating LML during calculations of the weighting of the criteria. CFA in the IBM SPSS AMOS V26 program has been applied to test the model's fit, validity, and reliability. The CFA approach successfully validated the proposed model, which can be used as a standardized measurement instrument by lean practitioners.

This study verifies that the Lean maturity measurement model consists of multiple dimensions, which were identified previously as 9 main axes (14 sub-axes). In theory, this paper contributes to creating a new way of thinking and better comprehending the dimensions of the Lean maturity measurement model by validating the identified axes. It has been shown that there is a need for an all-inclusive approach while measuring Lean maturity. One of the essential findings of the defined criteria for the lean maturity measurement model is the human factor. All criteria that are directly related to the human factor, such as Management and Leadership, Working Conditions, and People, show that the success of lean implementations is directly related to the motivation of the employees, adoption of lean methods, and involvement of the management team.

A model to measure the LML of the companies has been designed and used, and it has been validated with the CFA approach by examining model fit, reliability, and validity. This paper outlines a high-level model of lean maturity for companies. Since each organization is distinctive and unique, it is highly recommended to personalize a lean maturity measurement model that is tailored to its specific circumstances and constraints by taking into account the industry, the scale of the company, product type, product volume, production type and other particular requirements and strategies of the company. The essential factor for the successful implementation and achievement of the highest level (sustainability level) of Lean maturity in organizations is to draw a roadmap that represents a detailed transformation plan for the corporation.

To adopt the lean philosophy and to properly implement and develop lean tools, it is helpful to conduct a lean assessment using the lean checklist at regular intervals. As a recommendation, a soft assessment can be done twice a year with an internal auditor and a comprehensive check with an external auditor once a year. On the other hand, lean methods should be part of daily shop floor management. It is also recommended to develop a dynamic assessment system in line with changing needs over time by using the feedback of the previous assessments and by reviewing leanness results in comparison with performance.

5.1 | Implications for Research and Practice

Determining LMLs allows businesses to improve efficiency by examining their processes. Compliance with lean principles can increase effectiveness and efficiency by reducing waste and optimizing business processes. Having a lean manufacturing approach can provide businesses with a competitive advantage. Being able to respond quickly to customer demands and reducing costs allows us to get ahead in the market. Determining LMLs is essential to maintaining this competitive advantage. Lean principles can make business processes more flexible and adaptable. Businesses feel the need to assess their LML to quickly adapt to changing market conditions and increase their resilience.

In a dynamic production environment, there is a need to adapt to constantly changing conditions. Lean models offer the opportunity to adapt and optimize business processes by focusing on continuous improvement principles. Lean models often take a modular approach, which helps businesses focus on priority areas and respond quickly to changes. Modularity makes the application more manageable in a dynamic environment. Nowadays, technological advances can make it easier to implement lean models. Automation, data analysis, and other technological tools can support businesses in determining and improving their LMLs. Implementing models based on lean principles can provide a return on investment in the long term. As businesses see advantages such as cost savings, increased customer satisfaction, and operational efficiency, they can be rewarded for the time and resources they devote to these models.

As a result, implementing lean models in a dynamic manufacturing environment can be challenging. Still, the flexibility and continuous improvement-oriented nature of these models offer the potential to provide businesses with a competitive advantage.

The following essential findings of this study are of great value to researchers and practitioners by proposing and validating a measurement instrument to measure LML.

I. This research and the proposed MM are to help industry managers, engineers, researchers, and practitioners evaluate the leanness of companies.

II. The research contributes to developing theories in the new area of measuring LML. It aims to enhance comprehension of the different facets of a lean maturity evaluation model.

III. In the future, upcoming studies can provide a broader analysis of the literature on LMMs to provide a comprehensive account of research applications in this area.

IV. Practitioners can use the proposed instrument to measure the level of Lean maturity concerning the 9 main 14 sub-axes. This allows practitioners to develop a holistic approach to deploying the Lean maturity evaluating model, resulting in practical implementation.

V. The study's proposed measuring model can help other researchers use SEM to explore causal relationships between the axes of Lean maturity assessment.

VI. According to the specific requirements of organizations, the axes of the proposed LMM described in this study can be prioritized according to their relative importance in influencing organizational performance using different multi-criteria decision-making techniques.

VII. Since each organization is distinctive and unique, it is highly recommended to personalize a lean maturity measurement model that is tailored to its specific circumstances and constraints by taking into account the industry, the scale of the company, product type, product volume, production type and other specific requirements and strategies of the company.

VIII. Researchers and practitioners can use this work along with the developed instrument to study the effect of the axes of Lean maturity in influencing outcome variables such as complexity level, profitability (in %), delivery time, consumer satisfaction rate, organizational performance, agility, and sustainability.

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Appendix

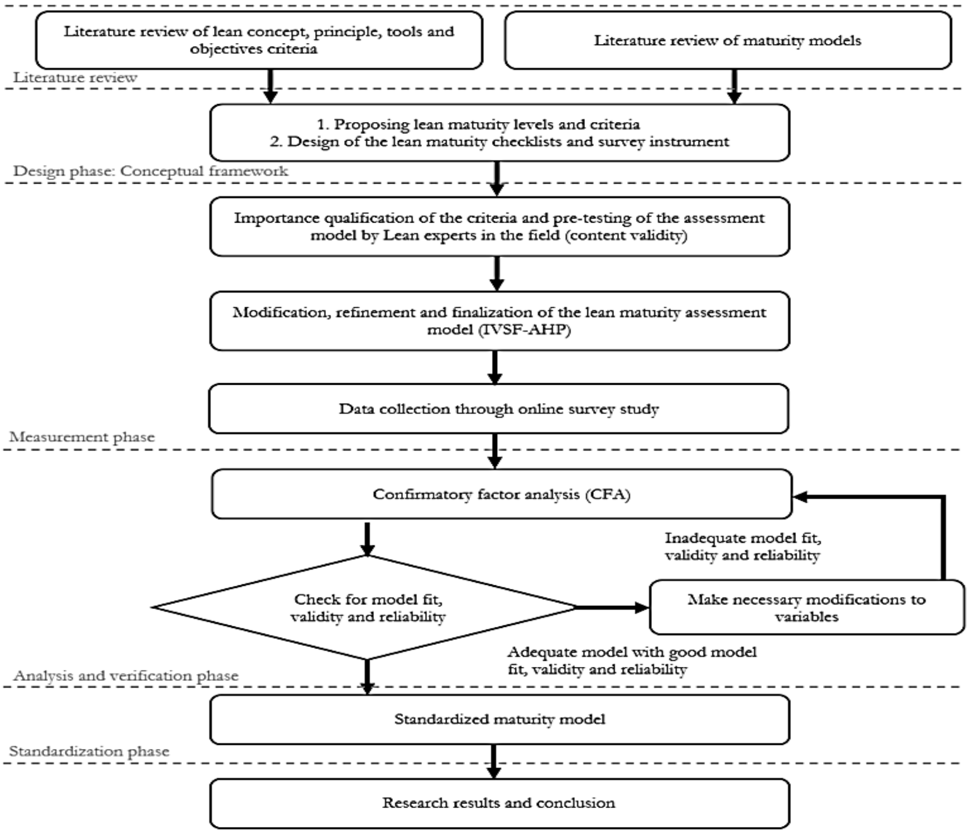

Fig. A1. General framework of the research methodology.

Table A1. Linguistic terms used for pairwise comparisons.

Linguistic terms	s˜ = ([μ−(x), μ+(x)], [ν−(x), ν+(x)], [I −(x), I +(x)])	Score Index
Absolutely more importance	([0.85, 0.95], [0.10, 0.15], [0.05, 0.15])	9
Very high importance	([0.75, 0.85], [0.15, 0.20], [0.15, 0.20])	7
High importance	([0.65, 0.75], [0.20, 0.25], [0.20, 0.25])	5
Slightly more importance	([0.55.0.65], [0.25, 0.30], [0.25, 0.30])	3
Equal importance	([0.50, 0.55], [0.45, 0.55], [0.30, 0.40])	1
Slightly low importance	([0.25, 0.30], [0.55, 0.65], [0.25, 0.30])	1/3
Low importance	([0.20, 0.25], [0.65, 0.75], [0.20, 0.25])	1/5

Table A2. An Example Survey Instrument (Checklist) to Measure LM and Scale.

Control item: Standard operating procedures Axis: 1 – Management and Leadership								
Checklist		**Score**						**Evidence**
		0	**1**	**2**	**3**	**4**	**N/A**	
1	Lean production systems coordinators/ lean production systems transformation leaders have been identified to manage lean production processes and provide support for lean practices.							
2	In order to implement lean thinking in the organization, goals are set with the support of leaders, process plans are made, and efforts are made to implement these plans. Leaders take an active role in this process.							
3	Management provides the necessary opportunities for employees to adopt lean thinking and to apply lean methods. Studies and training are organized on the subject.							
4	Management has developed a lean transformation strategy and is planning for it. Management aims to use resources efficiently and eliminate waste.							
5	Long-term vision, mission, goals, and responsibilities have been determined for lean production as the ultimate goal and for lean production.							
6	Leaders apply the Gemba walk, one of the lean guiding principles, to observe and identify the current situation on the ground and identify risk factors.							
7	In these audits, the lean expert acts as an external auditor.							
8	Management systematically identifies and monitors lean needs in products, processes, and operations.							
9	A lean production systems (PS) department was established to implement and execute lean production processes properly.							

Table A3. A literature review of Lean Maturity criteria.

Subject of Study	Used Criteria	Number of Considered Criteria	Author
A model for evaluating the degree of leanness of manufacturing firms	Elimination of waste, continuous improvement, zero defects, just-in-time deliveries, the pull of raw materials, multifunctional teams, decentralization, integration of functions, vertical information systems	9	[46]
A field study on measuring the lean maturity level in manufacturing firms in Turkey	Kanban, production planning and scheduling, setup reduction, industrial housekeeping (5S), reduction of work-in-process and inventory, visual controls, poka yoke, cellular manufacturing, supplier relations management, TPM, flexible workers, elimination of wastes	12	[2]
Examining the Association Between Leadership Styles and an Organization's Lean Manufacturing Maturity Level	Leadership style and management	1	[47]
A maturity assessment of lean development practices in manufacturing industry	Kanban, 5S, Kaizen, energy efficiency program, cellular manufacturing, poke-yoke, standardized work, visual stream mapping, plan do check action, statistical process control, SMED, JIT, total productive maintenance	13	[22]
Assessment of Lean Maturity Level in Manufacturing Cells	People, facility management, working conditions, production processes, quality, just-in-time, leadership	7	[48]
A literature review on lean maturity level tools	Continuous improvement (Kaizen), workload leveling (Heijunka), pull production (Kanban), visual management, single-minute exchange of die, 5S, total preventive maintenance, just in time, standardized work, value stream mapping, continuous production flow, supplier development, autonomation (Jidoka), cellular manufacturing, poka yoke, multifunctional teams, total quality management, training people, commitment of employees and management, challenging customers and suppliers, reduction of supply base, unit lots/reduction of production batches, empowerment, hoshin-kanri, root cause analysis, zero defects, reliable and tested technology, process mapping, radical improvement (Kaikaku), flexible information system, stocks replacement point, simulation	32	[24]
Developing an instrument to measure lean manufacturing maturity and its relationship with operational performance	Strategic planning, quality at sources, processes and tools, problem-solving, people, supplier integration, continuous improvement, customer focus	8	[49]
Lean manufacturing maturity model	Leadership, people, process, results	4	[50]

Table A4. Criteria and literature references.

#	Code	Criteria	Author	Model
1	C1	Management and leadership	[47]	MLQ and LESAT
2	C2	Quality		
2.1	C2.1	total quality management	[24]	Analysis of lean maturity level tools
2.2	C2.2	Standardization and standard work	[24]	Analysis of lean maturity level tools
2.3	C2.2	Jidoka	[24]	Analysis of lean maturity level tools
3	C3	JIT	[14]	A lean maturity model
4	C4	Lean techniques		
4.1	C4.1	Gemba and Kaizen	[22]	Maturity assessment of lean management tools
4.2	C4.2	Ergonomy and 5S	[22]	Maturity assessment of lean management tools
4.3	C4.3	Value stream mapping	[24]	Analysis of lean maturity level tools
4.4	C4.4	Waste and loss management	[46]	A lean maturity model
5	C5	Facility management	[14]	A lean maturity model
6	C6	Supplier relations management	[2]	Measurement of lean maturity level
7	C7	Production processes	[49]	Lean production maturity level measurement tool
8	C8	Working conditions	[14]	A lean maturity model
9	C9	People	[14]	A lean maturity model