

RESEARCH PAPER

Prioritizing leagile manufacturing implementation barriers in the context of Industry 4.0: an integrated framework for causal mapping in the automotive parts industry

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ABSTRACT

Goal: This study identifies, maps, and prioritizes barriers to leagile manufacturing implementation under Industry 4.0 in the Iranian automotive parts industry and distinguishes cause-type from effect-type barriers.

Design / Methodology / Approach: A literature review identified 28 barriers, while experts proposed three additional barriers. Judgments from 15 industrial managers, consultants, and academic experts were analyzed using fuzzy Delphi to screen barriers, DEMATEL to map direct and indirect influence relationships, and DANP to derive interdependent priority weights.

Results: Fuzzy Delphi retained 11 of 31 candidate barriers. DEMATEL showed that the most influential cause-type barriers concerned organizational management, leadership, employee training, and understanding of leagile concepts. DANP ranked ineffective organizational management, lack of employee training, lack of understanding of leagile concepts, and lack of top management commitment as the four most critical barriers. These upstream weaknesses were assessed as influencing downstream operational and technological problems.

Limitations of the investigation: The findings are based on subjective expert judgments collected within a single industry and country using a cross-sectional design. Therefore, the rankings may be context-dependent and may not capture changes in barrier relationships over time.

Practical implications: Automotive parts manufacturers should strengthen organizational readiness, leadership commitment, employee training, understanding of leagile principles, and performance measurement as foundations for flexibility and digitalization initiatives.

Originality / Value: This study treats leagile implementation barriers as an interdependent system and integrates screening, causal mapping, and priority weighting into a context-specific framework for allocating transformation resources under Industry 4.0.

Keywords: Leagile manufacturing; Industry 4.0; Implementation barriers; Fuzzy Delphi; DEMATEL–DANP.

1 INTRODUCTION

Manufacturing firms face growing competitive pressure to improve efficiency, agility, and operational performance in dynamic markets (Nawanir and Moshood, 2025). In manufacturing and supply chain contexts, performance improvement is commonly linked to quality, cost, delivery, waste reduction, and responsiveness (Núñez-Merino et al., 2020; Singh and Singh, 2024). At the same time, volatile demand, high product variety, shorter product life cycles, and changing

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customer requirements make responsiveness and flexibility central to agile and leagile manufacturing (Krishnamurthy and Yauch, 2007; Sutrisno et al., 2024). In leagile systems, the decoupling point separates upstream lean processes from downstream agile processes, and this upstream-downstream logic has also been applied in an automotive parts manufacturing case (Krishnamurthy and Yauch, 2007; Shahin and Jaber, 2011). In advanced manufacturing settings, Industry 4.0 technologies support information exchange, horizontal and vertical integration, real-time monitoring, and data-driven coordination across production and supply chain activities (Crnjac et al., 2017; Núñez-Merino et al., 2020; Ivanov et al., 2019). However, these technologies should not be treated as a stand-alone solution. Industry 4.0 implementation needs to be aligned with process improvement, organizational readiness, and lean-based continuous improvement rather than added to poorly organized processes (Crnjac et al., 2017; Singh and Singh, 2024; Torre et al., 2023). This makes organizational, workforce, and technological readiness relevant to leagile implementation, particularly as manufacturers combine lean-agile practices with increasing digital integration.

Although lean-based improvement can strengthen process discipline and efficiency, the traditional lean paradigm is primarily oriented to stable demand. It can be less suitable when markets require high responsiveness and product variety (Krishnamurthy and Yauch, 2007).

Agile manufacturing is commonly described as the ability to adapt to continuous and unexpected change by responding quickly and effectively to shifting markets and customer demands (Virmani et al., 2018). Achieving agility often involves holding inventory and capacity buffers to enable fast response, which can conflict with lean's low inventory efficiency objectives (Virmani et al., 2017).

Leagile manufacturing has therefore emerged as a hybrid approach that combines the efficiency orientation of lean with the responsiveness orientation of agile manufacturing (Krishnamurthy and Yauch, 2007; Mohaghegh and Größler, 2025; Razmi et al., 2015). In principle, leagile systems can support cost efficiency while enabling faster and more flexible responses to demand variability. In practice, however, their implementation requires firms to align planning and control routines, performance measurement, workforce capabilities, and technology use (Piotrowicz et al., 2023; Silva et al., 2024).

The automotive parts manufacturing industry provides a demanding setting for leagile implementation because suppliers must balance cost efficiency, quality, delivery reliability, product variety, and responsiveness to OEM requirements. In such a setting, leagile implementation must improve efficiency and flexibility without undermining operational viability.

Despite growing interest in lean, agile, and leagile systems, the barriers to implementing leagile manufacturing remain insufficiently understood in the automotive parts industry, particularly in emerging economy contexts. Existing studies have identified lean, agile, or leagile barriers, but less attention has been given to how these barriers influence one another and how managers should prioritize them when resources for transformation are limited. This gap is important because treating barriers as an isolated checklist may lead firms to address visible operational symptoms while neglecting upstream managerial and capability-related barriers.

The overall objective of this study is to identify, map, and prioritize barriers to leagile manufacturing implementation in the Iranian automotive parts industry under Industry 4.0 conditions. It addresses the following research questions:

- RQ1. Which barriers most critically hinder leagile manufacturing implementation?
- RQ2. Which barriers are classified as cause-type rather than effect-type?
- RQ3. How should managers prioritize limited resources across these barriers?

To answer these questions, barriers were gathered from the literature, refined by experts, screened using the fuzzy Delphi method, and analyzed using the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method and the DEMATEL-based analytic network process (DANP) to reveal influence relationships and relative priorities.

The paper proceeds as follows. Section 2 reviews Industry 4.0 and lean-agile integration, together with empirical studies on lean, agile, and leagile implementation barriers. Section 3 explains the research design and analytical procedures. Section 4 reports the findings from the fuzzy Delphi, DEMATEL, and DANP analyses. Section 5 interprets the results and discusses their theoretical and managerial implications. Section 6 summarizes the study, acknowledges its limitations, and identifies directions for future research.

2 LITERATURE REVIEW

2.1 Industry 4.0 and lean-agile integration

Industry 4.0 refers to the digital transformation of manufacturing through connected and data-driven technologies such as Industrial Internet of Things (IIoT), cloud computing, big data, simulation, and digital twins (Urquía et al., 2025). In these systems, machines, products, and resources exchange information and act autonomously, supported by horizontal and vertical integration and digital engineering. This enables continuous optimization and data-driven coordination along the value chain (Crnjac et al., 2017; Núñez-Merino et al., 2020; Horváth and Szabó, 2019). Implementing Industry 4.0 requires investments in technologies, infrastructure, and skills, along with organizational change and new forms of collaboration across functional boundaries (Ghobakhloo, 2018). Firms also need the capability to operate integrated digital systems and translate data-driven insights into operational decisions (Chen et al., 2023).

Industry 4.0 technologies can enhance supply chain visibility and coordination by enabling real-time monitoring and control of material and information flows, thereby supporting integrated operations and operational efficiency (Ivanov et al., 2019).

Systematic reviews suggest that Industry 4.0 technologies can improve lean cost competitiveness and support agility-related flexibility, allowing lean and agile approaches to coexist and reducing the efficiency-flexibility trade-off (Ding et al., 2023). Complementary evidence also indicates that integrating lean and Industry 4.0 can bring benefits and long-term competitive advantages (Saad et al., 2024).

Several studies suggest that lean principles, which emphasize process standardization, waste reduction, and flow improvement, provide an organizational platform for digitalization. Streamlined and stable processes are easier to automate and connect with Industry 4.0 technologies than fragmented, poorly managed operations. The notion of Lean 4.0 captures this complementarity by framing digital tools as enablers of lean maintenance and continuous improvement. Lean routines help focus data collection and analytics on reducing value-added losses (Torre et al., 2023). For leagile manufacturing, this complementarity is particularly relevant because digital connectivity, real-time information sharing, and integrated operations can support coordination between lean efficiency and agile responsiveness, provided that organizational readiness, workforce capabilities, and disciplined processes are in place.

Prior research in emerging economy manufacturing shows that lean initiatives often struggle due to organizational and managerial barriers, such as limited training, weak methodological understanding, and a lack of top management commitment (Upadhye et al., 2016). In emerging economy contexts, economic volatility and policy uncertainty may further constrain the expected performance benefits of lean-oriented improvement programs (Basu et al., 2021).

2.2 Empirical studies on lean, agile, and leagile implementation

Numerous studies have examined the implementation of lean manufacturing, as well as its barriers and critical success factors, across different industries and countries. In the Malaysian automotive parts industry, Nordin et al. (2010) identified barriers related to a lack of understanding of lean concepts and unfavorable shop-floor employee attitudes. In Indian manufacturing, a survey-based study similarly highlights managerial issues, limited training and employee involvement, and broader cultural obstacles such as resistance to change and weak understanding of lean methods (Kumar and Kumar, 2014). A study on Just-in-Time (JIT) implementation barriers similarly highlights the key role of managerial commitment, training, and cultural factors (Jadhav et al., 2014). Based on a review of papers on lean implementation in Brazilian enterprises, Pereira et al. (2017) grouped the reported obstacles into seven main categories: difficulties in understanding and using lean manufacturing, operational resistance, cultural differences, slow response to market, lack of top/senior management involvement, lack of middle management support, and lack of resources to invest.

In the context of manufacturing implementation, barriers can be understood as challenges and impediments that restrict the adoption and effectiveness of improvement practices in manufacturing processes (Aher et al., 2025). Previous manufacturing frameworks have also been criticized for being incomplete, abstract, or insufficiently connected to the organizational context in which implementation takes place (Anand and Kodali, 2010). Therefore, examining leagile implementation requires more than listing relevant obstacles; it requires a structured approach that considers how barriers influence one another within a specific organizational and industrial context.

Pereira and Tortorella (2018) examined the relationships among lean practices, critical success factors, and implementation barriers in a small electronics manufacturer. Using qualitative methods and AHP, they identified employee commitment and motivation, along with education and training, as the most important factors. The study also noted that these relationships were analyzed linearly and that the systemic nature of lean implementation was not fully captured. The present study takes a different approach by examining how leagile implementation barriers influence one another and distinguishing cause-type from effect-type barriers.

Research on leagile manufacturing and leagile supply chains is still limited, but interest has increased in recent years. Rahiminezhad Galankashi and Helmi (2016) developed an assessment framework for leagile supply chain strategies that identifies and ranks operational activities and categorizes them across four key performance dimensions: cost, quality, service level, and lead time. In Indian manufacturing industries, Virmani et al. (2017) identified and ranked 17 barriers to leagile implementation using a questionnaire survey, and then used ISM and MICMAC to map their interrelationships and distinguish driving and dependent barriers. Virmani et al. (2018) used fuzzy DEMATEL to distinguish causal success factors such as strategic and human resource management, customer and market sensitivity, flexible production systems, and information technology from effect factors such as training, design, supply chain management, and reconfigurability. Li et al. (2020) examined leagile supplier selection in the Chinese textile industry using DEMATEL to map causal relationships among leagile-oriented supplier criteria. Narkhede et al. (2020) used an ISM and DEMATEL approach and identified ineffective organizational management and limited experience with advanced technologies as critical barriers to leagile manufacturing in original equipment manufacturers. Table 1 summarizes and compares the main characteristics and findings of related studies on leagile implementation and barriers.

Table 1 - Comparison of previous studies on leagile implementation and related barriers

Study	Context and focus	Method	Main findings
Rahiminezhad Galankashi and Helmi (2016)	Assessment of operational activities in leagile supply chain strategies	Literature review, expert judgment, AHP, and NGT	Identified, ranked, and categorized operational activities across major supply chain drivers and leagility dimensions.
Virmani et al. (2017)	Leagile implementation barriers in Indian manufacturing	Questionnaire survey, ISM, and MICMAC	Identified 17 barriers. Several managerial and resource-related barriers showed high driving power.
Virmani et al. (2018)	Critical success factors for leagile manufacturing in Indian manufacturing	Questionnaire survey and fuzzy DEMATEL	Classified 15 factors into cause and effect groups. Strategic, HR, and knowledge/IT management were among the cause factors.
Narkhede et al. (2020)	Lean-agile implementation barriers in Indian OEMs	Expert input, ISM, MICMAC, and DEMATEL	Ineffective organizational management and limited experience with technology adoption emerged as highly influential barriers.
Srinivas et al. (2022)	Sustainable lean-agile implementation drivers and barriers in OEMs	Systematic literature review and content analysis of 50 studies	Identified 165 drivers and barriers in 14 categories, with managerial, organizational, workforce, technological, and financial issues recurring frequently.
Mohaghegh and Größler (2025)	Leagile supply chain practices and sustainable business performance	Literature review, semi-structured expert interviews, TISM, and MICMAC	Developed a 10-level hierarchical model linking leagile practices with economic, environmental, and social performance.
Present study	Leagile implementation barriers in the Iranian automotive parts industry in an Industry 4.0 context	Fuzzy Delphi, DEMATEL, and DANP	Retained 11 of 31 candidate barriers and combined causal mapping with interdependent prioritization. Ineffective

	organizational management ranked highest overall. Training had the largest positive relation value, while technological upgrading had the most negative relation value.
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Source: The author himself.

As shown in Table 1, prior studies have examined leagile implementation from complementary perspectives, including barrier ranking, structural hierarchy, cause-effect analysis, and literature-based categorization. The present study links fuzzy Delphi screening with DEMATEL causal mapping and DANP-based interdependent weighting. This allows contextual relevance, cause-effect classification, and relative priority to be considered together while distinguishing overall priority from a barrier’s role in the influence structure.

3 METHOD

3.1 Research design

This study applied an integrated fuzzy Delphi-DEMATEL-DANP approach to identify, map, and prioritize barriers to leagile manufacturing implementation in the Iranian automotive parts manufacturing industry. The research process comprised four stages. First, the problem was defined, and an initial list of candidate barriers was developed through the literature review and contextual assessment. Second, the fuzzy Delphi method was used to refine and validate the candidate barriers. Third, DEMATEL was applied to map the influence structure among the retained barriers and distinguish cause-type from effect-type barriers. Fourth, DANP was used to derive priority weights under an interdependent structure (Kuo et al., 2015; Lin et al., 2025; Hu et al., 2018).

3.2 Expert panel and data collection

The study drew on judgments from 15 experts selected purposively based on their relevant professional experience and familiarity with leagile implementation or manufacturing transformation. Table 2 summarizes the composition and qualifications of the expert panel. The industrial managers and consultants represented two automotive manufacturers and one automotive parts manufacturer, while the academic experts were affiliated with the Faculty of Automotive Engineering at a technical university.

The expert panel included complementary academic, managerial, and consulting perspectives from the Iranian automotive parts sector. Accordingly, the findings reflect expert judgment within the selected industrial context and should not be interpreted as representative of the entire Iranian automotive parts sector.

Table 2 - Expert panel composition

Expert group	Number	Organizational context	Level of responsibility	Minimum relevant experience	Relevant knowledge and experience
Senior academic	3	Faculty of Automotive Engineering at a technical university	Senior academic or technical roles	8 years	Familiarity with automotive parts production and leagile implementation
Industrial managers	6	Automotive OEMs and parts manufacturers	Management roles in manufacturing operations	10 years	Experience in production line transformation and manufacturing change initiatives
Consultants	6	Automotive OEMs and parts manufacturers	Consulting roles in	7 years	Experience in production line transformation

	manufacturing improvement	and manufacturing change initiatives
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Source: The author himself.

The literature review informed the initial barrier list, while structured questionnaires were used to collect fuzzy importance ratings and pairwise influence judgments for DEMATEL. Delphi convergence was assessed across rounds using changes in defuzzified scores as the stopping criterion.

3.3 Identification of candidate leagile barriers

The initial candidate list was developed from barriers reported in prior lean, agile, leagile or lean-agile, and related manufacturing studies, including technological and organizational challenges associated with Industry 4.0 transformation. Industry 4.0 informed the composition of the initial barrier pool, while the relevance of the candidates to leagile implementation in the Iranian automotive parts industry was subsequently assessed by the expert panel. Representative literature supporting each literature-derived candidate barrier is provided in Appendix Table A5.

During Round 1, experts evaluated the 28 literature-derived barriers, reviewed their contextual relevance, refined the descriptions of closely related barriers where needed, and proposed three additional barriers. The 10 barriers retained in Round 1, together with the three barriers suggested by experts, were evaluated in Round 2. Eleven barriers were retained and reassessed in Round 3, with convergence assessed by comparing their defuzzified scores across Rounds 2 and 3. Figure 1 summarizes the research process.

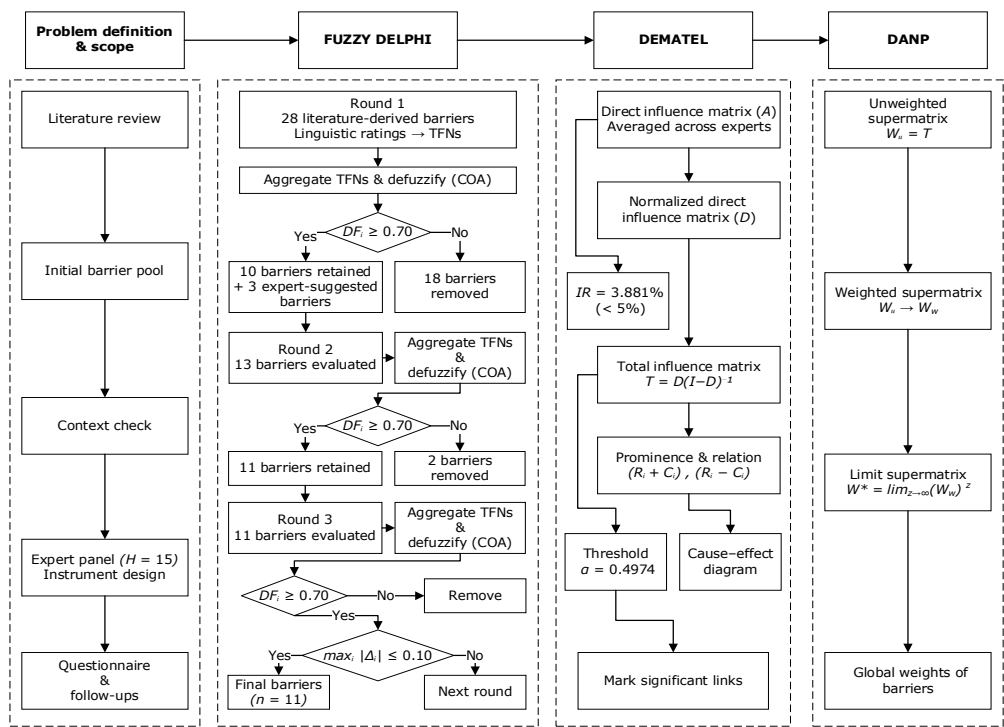


Figure 1 - Research methodology framework of the fuzzy Delphi-DEMATEL-DANP analysis

Source: The author himself.

3.4 Fuzzy Delphi method

The fuzzy Delphi method was employed to refine and screen the initial set of candidate barriers by incorporating expert judgments under uncertainty. Compared with the traditional Delphi method, fuzzy Delphi allows experts to express judgments through linguistic ratings that are converted into fuzzy numbers, thereby capturing uncertainty and subjectivity in expert evaluations (Habibi et al., 2015).

Experts evaluated the importance of each barrier using a five-point linguistic scale, where each linguistic term is represented by a triangular fuzzy number (TFN).

The linguistic scale and its corresponding triangular fuzzy numbers are shown in Table 3.

Table 3 - Linguistic scale and corresponding triangular fuzzy numbers

Term	Very unimportant	Unimportant	Moderate	Important	Very important
TFN	(0.00,0.00,0.25)	(0.00,0.25,0.50)	(0.25,0.50,0.75)	(0.50,0.75,1.00)	(0.75,1.00,1.00)

Source: Adapted from Habibi et al. (2015).

Let $i = 1, \dots, n$ index the barriers and $k = 1, \dots, H$ index the experts. The fuzzy rating of expert k for barrier i is denoted by:

$$\tilde{f}_i^{(k)} = (l_i^{(k)}, m_i^{(k)}, u_i^{(k)}) \quad (1)$$

3.4.1 Aggregating expert fuzzy ratings

The fuzzy opinions of the experts are aggregated for each barrier using the simple fuzzy average (Habibi et al., 2015):

$$\tilde{F}_i = (L_i, M_i, U_i) = \left(\frac{1}{H} \sum_{k=1}^H l_i^{(k)}, \frac{1}{H} \sum_{k=1}^H m_i^{(k)}, \frac{1}{H} \sum_{k=1}^H u_i^{(k)} \right) \quad (2)$$

3.4.2 Defuzzification

To obtain a crisp importance score for each barrier, the aggregated TFNs are defuzzified using the centroid, or center of area (COA) method (Habibi et al., 2015; Ebrahimi and Bridgelall, 2021).

$$DF_i = \frac{L_i + M_i + U_i}{3} \quad (3)$$

3.4.3 Selecting the threshold and screening criteria

Following prior fuzzy Delphi applications, a cutoff threshold of $\tau = 0.70$ was applied, and only items with $DF_i \geq \tau$ were retained (Wu and Fang, 2011; Habibi et al., 2015; Ebrahimi and Bridgelall, 2021). This cutoff is also consistent with the five-point linguistic scale used in this study (Table 3), as it lies between the centroid values of the “moderate” (0.50) and “important” (0.75) categories and is closer to the latter. Accordingly, retained barriers had aggregated evaluations approaching the “important” category. For multi-round Delphi, convergence was assumed when the absolute difference in defuzzified scores between consecutive rounds was ≤ 0.10 for all items (Ebrahimi and Bridgelall, 2021). As an additional threshold sensitivity check, the stability of the final fuzzy Delphi barrier set was examined by applying stricter cutoff values of 0.725 and 0.750 to the Round 3 crisp scores. The retained barriers were then used as inputs to the DEMATEL–DANP analysis.

3.5 DEMATEL-based analytic network process (DANP)

To capture the interdependencies among the validated barriers and to convert expert judgments into a system of priority weights, the DANP method was employed (Kuo et al., 2015; Hu et al., 2018). The Decision-Making Trial and Evaluation Laboratory (DEMATEL) method was first applied to estimate direct and indirect influence relationships among the barriers and distinguish cause-type from effect-type barriers (Kuo et al., 2015; Si et al., 2018). The resulting total influence matrix was then used to construct the unweighted supermatrix to derive priority weights that account for feedback and interdependence among the barriers (Hu et al., 2018; Kuo et al., 2015).

3.5.1 Direct influence matrix construction

Experts assessed the degree to which each barrier influenced the others. For any ordered pair (i, j) , expert k assigned a score x_{ij}^k to the influence of barrier i on barrier j using a 0–4 scale where 0

indicates no influence and 4 indicates very strong influence, consistent with common DEMATEL applications (Li et al., 2020; Ojha, 2023).

Because a barrier does not directly influence itself, the diagonal elements were set to zero. Therefore, $x_{ii}^k = 0$ for all experts. Let H denote the number of experts. The aggregated direct influence matrix $A = [a_{ij}]$ was obtained by averaging expert judgments using the arithmetic mean (Si et al., 2018):

$$a_{ij} = \frac{1}{H} \sum_{k=1}^H x_{ij}^k \quad (4)$$

Here a_{ij} represents the average direct influence of barrier i on barrier j across all experts, and $a_{ii} = 0$. Let n denote the number of final barriers obtained from the fuzzy Delphi phase.

3.5.2 Reliability and stability of expert judgments

To assess the reliability and stability of the aggregated group direct influence matrix A used in the DEMATEL–DANP procedure, a sample stability inconsistency ratio (IR) is computed by examining the sensitivity of the averaged direct influence values to the inclusion of an additional expert. A low IR indicates stable group judgments (Shen et al., 2014).

Let H denote the number of experts and n denote the number of barriers. Let $a_{ij}^{(H)}$ be the (i, j) entry of the direct influence matrix averaged over all H experts, and $a_{ij}^{(H-1)}$ be the corresponding entry averaged over the first $H-1$ experts. The IR is calculated as:

$$IR = \frac{1}{n(n-1)} \sum_{i=1}^n \sum_{\substack{j=1 \\ j \neq i}}^n \frac{|a_{ij}^{(H)} - a_{ij}^{(H-1)}|}{a_{ij}^{(H)}} \times 100 \quad (5)$$

If $a_{ij}^{(H)} = 0$, the corresponding term was omitted from the calculation.

An IR below 5% is considered acceptable. In this study, the calculated IR was 3.881% ($< 5\%$), confirming that the aggregated expert evaluations are sufficiently stable for the subsequent DEMATEL–DANP analysis (Shen et al., 2014).

3.5.3 Normalization of the direct influence matrix

To ensure the convergence of the DEMATEL process, the direct influence matrix A is normalized by a scaling factor S , computed as (Sun et al., 2023; Huang et al., 2024):

$$S = \frac{1}{\max\{\max_{1 \leq i \leq n} \sum_{j=1}^n a_{ij}, \max_{1 \leq j \leq n} \sum_{i=1}^n a_{ij}\}} \quad (6)$$

The normalized direct influence matrix D is then obtained by:

$$D = A \cdot S \quad (7)$$

This scaling bounds the maximum row/column sums of matrix D to at most 1 and supports the convergence needed to compute the DEMATEL total relation matrix.

3.5.4 Total influence matrix and cause–effect analysis

The total influence matrix T captures both direct and indirect effects among barriers and is computed using the standard DEMATEL formulation (Huang et al., 2024; Li et al., 2020):

$$T = D + D^2 + \dots + D^h = \sum_{h=1}^{\infty} D^h = D(I - D)^{-1} \quad (8)$$

Here I is the identity matrix. Each element t_{ij} of matrix T represents the overall influence (direct and indirect) of barrier i on barrier j .

For each barrier i , the row sum and column sum of matrix T are defined as:

$$R_i = \sum_{j=1}^n t_{ij}, i = 1, \dots, n \quad (9)$$

$$C_i = \sum_{j=1}^n t_{ji}, i = 1, \dots, n \quad (10)$$

Here, R_i reflects the overall influence given by barrier i on other barriers, whereas C_i represents the overall influence received by barrier i . The sum $(R_i + C_i)$, referred to as prominence, indicates the overall level of involvement of barrier i in the system. Larger values signify greater importance and vice versa (Nawaz and Ali, 2020). The difference $(R_i - C_i)$, referred to as the relation index, classifies barriers with positive values as causes, whereas those with negative values are classified as effects (Ojha, 2023; Hu et al., 2018; Si et al., 2018). Accordingly, the DEMATEL cause-effect classification reflects influence patterns based on expert judgments within the modeled barrier structure.

3.5.5 Cause-effect diagram

To visualize the cause-effect structure, a two-dimensional diagram was constructed in which the horizontal axis represents prominence $(R_i + C_i)$ and the vertical axis represents the relation index $(R_i - C_i)$. Each barrier i is plotted as a point with coordinates $(R_i + C_i, R_i - C_i)$ (Si et al., 2018).

To highlight the most relevant relations and filter out negligible effects, the threshold value α was computed as the arithmetic mean of all elements in the total influence matrix $T = [t_{ij}]$ (Cherapanukorn et al., 2025; Nawaz and Ali, 2020), and off-diagonal relations with $t_{ij} > \alpha$ were highlighted in bold in the T matrix (Lin et al., 2025).

$$\alpha = \frac{\sum_{i=1}^n \sum_{j=1}^n t_{ij}}{N} \quad (11)$$

Here $N = n^2$ is the number of elements in T .

3.5.6 Single-cluster DANP supermatrix formulation

In the DANP method, the DEMATEL total influence (also called the total relation) matrix can be treated as the unweighted supermatrix in the analytic network process (ANP) framework (Liang et al., 2023; Sun et al., 2023).

Accordingly, in the single-cluster setting of this study, the DEMATEL total influence matrix T was used as the unweighted supermatrix, $W_u = T$.

The weighted supermatrix W_w is obtained by column-wise normalization of T by dividing each element by the sum of its column, so that each column sums to one (Sun et al., 2023).

$$W_w = W_u \Delta^{-1} \quad (12)$$

Here Δ is a diagonal matrix with diagonal elements representing the column sums of W_u :

$$\Delta_{jj} = \sum_{i=1}^n (W_u)_{ij} \quad (13)$$

Each column of W_w sums to 1, and the elements of $W_w = [w_{ij}]_{n \times n}$ are computed as:

$$w_{ij} = \frac{(W_u)_{ij}}{\sum_{k=1}^n (W_u)_{kj}} = \frac{t_{ij}}{\sum_{k=1}^n t_{kj}} \quad (14)$$

3.5.7 Limiting supermatrix and global barrier weights

To obtain the steady-state influence of each barrier, the weighted supermatrix is raised to successive powers until it converges (Upadhyay and Shukla, 2025; Lin et al., 2025):

$$W^* = \lim_{z \rightarrow \infty} (W_w)^z \quad (15)$$

Once convergence is achieved, the entries in each row of $(W_w)^z$ tend to become identical across columns (Sun et al., 2023). The resulting column vector contains the global priority weights $\mathbf{w} = (w_1, \dots, w_n)^T$, satisfying:

$$\sum_{i=1}^n w_i = 1, w_i \geq 0 \quad (16)$$

These weights reflect the importance of each leagile barrier and are used for further analysis and interpretation.

4 RESULTS

4.1 Fuzzy Delphi analysis

Based on the literature review, an initial list of 28 potential barriers to implementing leagile manufacturing systems was identified. Experts evaluated these barriers using a fuzzy Delphi questionnaire with a five-point linguistic scale. Three additional barriers were suggested, bringing the total to 31 candidate barriers. Over three rounds, the list was refined to 11 barriers. Using the screening threshold ($\tau = 0.70$) and the convergence criterion described in Section 3.4, defined as an absolute difference of ≤ 0.10 between defuzzified scores in two consecutive rounds, all 11 barriers satisfied the acceptance and convergence conditions after Round 3 (Table 4).

Table 4 - Final Fuzzy Delphi screening results and convergence (rounds 2-3)

Barrier name	Code	Aggregated TFN (r_3)	Crisp score (r_3)	Absolute difference $ r_3 - r_2 $
Lack of employee training	B1	(0.567,0.817,0.983)	0.789	0.014
Inadequate use of employee empowerment	B2	(0.517,0.767,0.967)	0.750	0.000
Lack of benchmarking and standardization	B3	(0.500,0.750,0.933)	0.728	0.017
Poor planning	B4	(0.567,0.817,0.950)	0.778	0.000
Ineffective organizational management	B5	(0.567,0.817,0.967)	0.784	0.057
Lack of top management commitment	B6	(0.533,0.783,0.950)	0.755	0.051
Lack of flexibility	B7	(0.517,0.767,0.933)	0.739	0.000
Employee resistance to change	B8	(0.517,0.767,0.917)	0.734	0.045
Absence of an appropriate leagile performance measurement system	B9	(0.533,0.783,0.933)	0.750	0.060
Lack of technological upgrading and innovation	B10	(0.517,0.767,0.917)	0.734	0.084
Lack of understanding of leagile concepts	B11	(0.567,0.817,0.983)	0.789	0.018

Source: The author himself.

Note: Only the 11 barriers retained in Round 2 were reassessed in Round 3.

The threshold-sensitivity check showed that increasing the cutoff from 0.700 to 0.725 did not change the retained barrier set. At a cutoff of 0.750, seven barriers remained (B1, B2, B4, B5, B6, B9, and B11), while B3, B7, B8, and B10 fell below the stricter threshold (Appendix Table A6).

The four highest DANP-weighted barriers in the baseline model (B5, B1, B11, and B6) remained in the retained set at the 0.750 cutoff.

4.2 DEMATEL analysis: cause-effect structure of barriers

The direct influence matrix, obtained by averaging the judgments of the 15 experts, is provided in Appendix Table A1. This matrix was normalized according to Equations 6 and 7, and the total influence matrix was computed using Equation 8. The resulting total influence matrix is presented in Table 5.

Table 5 - Total influence matrix (T)

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11
B1	0.436	0.596	0.599	0.593	0.569	0.502	0.575	0.543	0.499	0.646	0.597
B2	0.413	0.379	0.466	0.485	0.450	0.404	0.491	0.459	0.353	0.510	0.429

B3	0.411	0.460	0.436	0.513	0.517	0.463	0.484	0.438	0.481	0.533	0.493
B4	0.475	0.495	0.515	0.459	0.542	0.482	0.517	0.440	0.423	0.577	0.505
B5	0.546	0.602	0.610	0.646	0.522	0.561	0.581	0.544	0.528	0.659	0.584
B6	0.481	0.511	0.537	0.578	0.558	0.402	0.520	0.454	0.440	0.560	0.503
B7	0.415	0.464	0.494	0.509	0.502	0.445	0.408	0.458	0.386	0.537	0.458
B8	0.454	0.504	0.519	0.527	0.526	0.451	0.541	0.388	0.399	0.558	0.488
B9	0.433	0.470	0.554	0.517	0.508	0.431	0.492	0.429	0.367	0.571	0.510
B10	0.412	0.452	0.512	0.490	0.453	0.397	0.473	0.408	0.416	0.431	0.439
B11	0.505	0.565	0.585	0.597	0.598	0.518	0.552	0.501	0.513	0.609	0.470

Source: The author himself.

Note: Bold values indicate significant relations where $t_{ij} > \alpha$.

The computed threshold for the total influence matrix was $\alpha = 0.4974$. Therefore, only matrix entries t_{ij} exceeding α were retained to identify significant relations, as highlighted in Table 5.

The row and column sums of the total influence matrix were then calculated to obtain the prominence and relation values. Table 6 presents these values and the resulting cause–effect classification.

Table 6 - Prominence, relation, and cause–effect classification of barriers

Barrier code	R_i	C_i	$(R_i + C_i)$	$(R_i - C_i)$	Type
B1	6.157	4.981	11.138	1.175	Cause
B2	4.840	5.497	10.338	-0.657	Effect
B3	5.229	5.827	11.056	-0.597	Effect
B4	5.430	5.914	11.344	-0.484	Effect
B5	6.382	5.746	12.127	0.636	Cause
B6	5.545	5.056	10.602	0.489	Cause
B7	5.076	5.634	10.710	-0.558	Effect
B8	5.353	5.063	10.416	0.291	Cause
B9	5.283	4.806	10.089	0.477	Cause
B10	4.883	6.189	11.073	-1.306	Effect
B11	6.011	5.477	11.487	0.534	Cause

Source: The author himself.

Based on DEMATEL, B5 shows the highest dispatching power ($R_i = 6.382$) and the greatest overall prominence ($R_i + C_i = 12.127$), indicating its central role in the influence structure. In contrast, B10 shows the highest receiving power ($C_{10} = 6.189$) and the most negative relation value ($R_i - C_i = -1.306$), suggesting that it is the most affected barrier. Moreover, B1 has the largest positive relation value ($R_i - C_i = 1.175$), indicating that it occupies the strongest cause-type position. The cause–effect structure of leagile implementation barriers is illustrated in Figure 2.

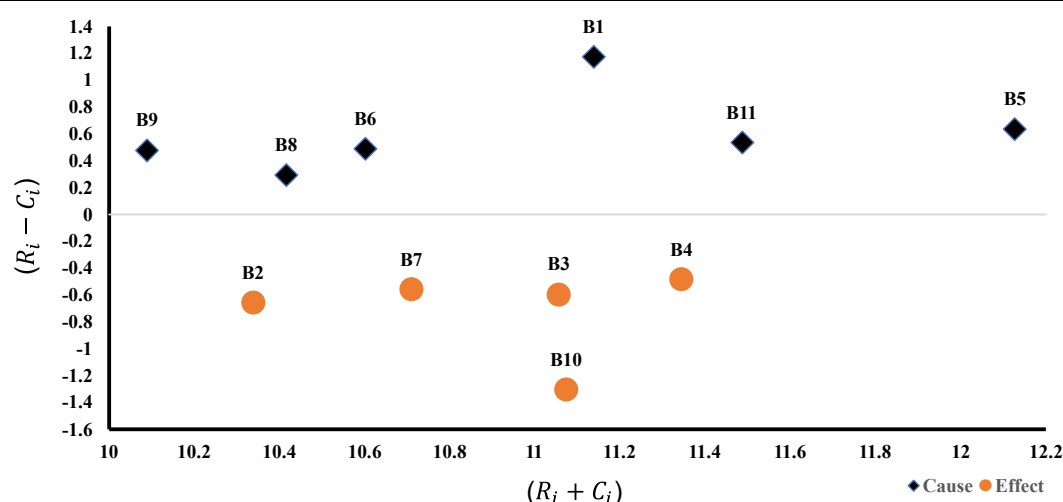


Figure 2 - Cause-effect diagram for leagile implementation barriers

Source: The author himself.

4.3 DANP-based weights and ranking of barriers

Following the single-cluster DANP procedure described in Section 3.5.6, the total relation matrix T was column-normalized to form the weighted supermatrix (Upadhyay and Shukla, 2025; Sun et al., 2023).

The weighted supermatrix was raised to successive powers until convergence at $z = 5$, when its columns became identical to four decimal places. Global priority weights were extracted from the limit supermatrix. Appendix Tables A3 and A4 report the weighted and limit supermatrices, while Table 7 presents the final weights and rankings.

Table 7 - Final weights and ranking of barriers

Barrier code	Final weight	Rank
B1	0.1019	2
B2	0.0804	11
B3	0.0872	8
B4	0.0904	5
B5	0.1060	1
B6	0.0921	4
B7	0.0844	9
B8	0.0888	6
B9	0.0876	7
B10	0.0813	10
B11	0.0999	3

Source: The author himself.

5 DISCUSSION

The DEMATEL-DANP results indicate that leagile implementation barriers in the Iranian automotive parts industry are structured around a managerial and human-capability core. Ineffective organizational management, lack of employee training, lack of understanding of leagile concepts, and lack of top management commitment are highly ranked barriers that occupy upstream positions relative to downstream operational and technological problems. This pattern suggests that leagile transformation should be treated as an organizational change process rather than as a purely technical improvement program.

The combined results distinguish structural centrality from cause-effect role. Ineffective organizational management (B5) received the highest DANP weight and the greatest prominence, indicating that it is the most structurally central barrier, whereas lack of employee training (B1) had the largest positive relation value, indicating that it occupies the strongest cause-type position.

In contrast, lack of technological upgrading and innovation (B10) had the highest receiving power and the most negative relation value, placing it in the strongest effect-type position within the DEMATEL structure.

Prior lean and JIT implementation studies similarly identify lack of top management commitment, limited training and employee involvement, weak methodological understanding, unfavorable employee attitudes, cultural barriers, employee resistance, and planning-related problems as recurring obstacles in manufacturing contexts (Upadhye et al., 2016; Nordin et al., 2010; Kumar and Kumar, 2014; Jadhav et al., 2014). The present findings partly align with earlier leagile studies. Virmani et al. (2017) emphasized training, resistance to change, and management-related barriers, while Narkhede et al. (2020) identified ineffective organizational management and technology-related barriers as major drivers. In the present study, organizational management remains central, but employee training occupies the strongest cause-type position and technological upgrading the strongest effect-type position, indicating some context-dependent differences in the DEMATEL cause–effect pattern.

The effect-type barriers identified in this study, including inadequate use of employee empowerment (B2), lack of benchmarking and standardization (B3), poor planning (B4), lack of flexibility (B7), and lack of technological upgrading and innovation (B10), should therefore not be treated only as isolated operational problems. Rather, they occupy downstream positions relative to organizational management, employee capability, leadership commitment, and conceptual understanding within the DEMATEL structure. This interpretation is consistent with the logic of lean implementation research, where operational barriers such as high inventory, high rejection rate, high lead time, and high setup time are treated as dependent barriers, while lack of top management commitment and lack of employee involvement and training show strong driving power (Upadhye et al., 2016). For managers, this means that isolated investments in technical fixes, flexibility initiatives, or technology upgrading may have limited impact if the upstream managerial and learning conditions remain weak.

The present findings can also be compared with previous studies on barriers to Industry 4.0 adoption. Ben Ruben et al. (2023) identified lack of top management commitment and inadequate training as the main driving barriers. Hossain et al. (2023) identified inadequate technical knowledge of Industry 4.0 as the most crucial barrier at the base level of their ISM model, while infrastructure insufficiency, the requirement of high investment, and inadequate workforce skills were among the linkage barriers.

In this study, lack of technological upgrading and innovation (B10) occupied the strongest effect-type position, while lack of employee training (B1) and lack of top management commitment (B6) were classified as cause-type barriers. The total influence matrix further shows that B10 receives substantial influence from B5, B1, B11, and B6. The Iranian automotive industry has been characterized by several conditions, including ineffective technology transfer, diverse technological areas, high tacit knowledge, extensive backward linkages, and an underdeveloped domestic supply chain (Minaee et al., 2021). In addition, weaknesses in the managerial, human, and knowledge aspects of technological capability were identified in most of the assessed Iranian automotive parts manufacturers (Mohammadi et al., 2014). These findings help explain the present influence structure, in which technological upgrading appears downstream of organizational and workforce-related barriers.

Candidate barriers related to technology, interorganizational coordination, organizational practices, and resources, including lack of information technology facilities, lack of supplier integration, lack of advanced production facilities, lack of continuous improvement culture, weak supplier–customer cooperation, and initial capital and budget constraints, did not meet the fuzzy Delphi threshold.

Some of these rejected barriers, particularly those related to technology, interorganizational coordination, and financial resources, are also discussed in the broader Industry 4.0 literature. In the present fuzzy Delphi screening, however, they did not reach the retention threshold, suggesting that experts placed greater relative emphasis on organizational, managerial, and workforce-related barriers to leagile implementation in the studied context. The screening results thus reflect context-specific relative priorities rather than the general importance of these barriers across manufacturing settings. The four barriers with the highest DANP weights in the baseline model (B5, B1, B11, and B6) remained in the retained set even when the fuzzy Delphi cutoff was increased to 0.750.

6 CONCLUSION

This study examined barriers to implementing leagile manufacturing in the Iranian automotive parts industry. Using an integrated fuzzy Delphi–DEMATEL–DANP approach, the study identified

the key barriers, mapped their influence relationships, and derived their relative priorities. The results indicate a cause-type group dominated by managerial and human-capability barriers that occupy upstream positions relative to operational and technological barriers within the DEMATEL structure.

Based on the DANP priority weights, ineffective organizational management, lack of employee training, lack of understanding of leagile concepts, and lack of top management commitment were the four highest-priority barriers.

6.1 Theoretical and managerial implications

This study contributes to leagile manufacturing research by combining barrier screening, cause-effect analysis, and prioritization within a single framework. The findings show that a barrier's overall priority does not necessarily correspond to its cause-effect role within the DEMATEL structure. Ineffective organizational management received the highest overall priority, whereas lack of employee training had the largest positive relation value. Accordingly, leagile implementation barriers should be considered in terms of both overall priority and cause-effect role within the influence structure. In the context studied, managerial and workforce-related barriers primarily occupied cause-type positions, while technological upgrading occupied an effect-type position. This pattern suggests that organizational and human-related conditions should receive early managerial attention when planning technological upgrading in the studied context.

For managers, the findings suggest a phased approach. First, firms should strengthen organizational management, top management commitment, employee training, and a shared understanding of leagile principles to establish organizational readiness. Second, these foundations should be reinforced through performance measurement, employee empowerment, benchmarking and standardization, planning, and flexibility. Once these organizational and operational capabilities are in place or being strengthened, technological upgrading can be pursued more effectively as part of Industry 4.0 transformation. In this phase, digital technologies reinforce process discipline, responsiveness, and organizational capability rather than substitute for them.

6.2 Limitations and future research

This study has several limitations. First, the findings are based on expert judgments from a single industry and country, which may limit their generalizability. The study also did not use independent operational or performance data to validate the relationships identified among the barriers. Second, fuzzy Delphi and DEMATEL-DANP rely on subjective evaluations and methodological choices, including the linguistic scale, defuzzification rule, convergence criterion, and influence threshold; alternative specifications may produce different retained barriers or priority weights. Third, the cross-sectional design cannot capture how barrier relationships evolve as firms progress through leagile implementation. Future studies should test the framework using larger, multi-industry, and multi-country samples, triangulate expert judgments with interviews across organizational levels and objective performance data, and employ longitudinal designs. Survey-based studies and structural equation modeling could also examine whether the identified upstream barriers predict implementation outcomes across broader populations.

REFERENCES

- Aher, D.H., Ubale, S. and Ubale, D.S. (2025), "Analysis of sustainable lean manufacturing implementation in Pune region manufacturing industries", *Journal of Advanced Manufacturing Systems*, Vol. 24, No. 4, pp. 769-790, doi: 10.1142/s0219686725500337
- Anand, G. and Kodali, R. (2010), "Analysis of lean manufacturing frameworks", *Journal of Advanced Manufacturing Systems*, Vol. 9, No. 1, pp. 1-30, doi: 10.1142/s0219686710001776.
- Basu, P., Chatterjee, D., Ghosh, I. and Dan, P.K. (2021), "Lean manufacturing implementation and performance: the role of economic volatility in an emerging economy", *Journal of Manufacturing Technology Management*, Vol. 32, No. 6, pp. 1188-1223, doi: 10.1108/JMTM-12-2019-0455.
- Ben Ruben, R., Rajendran, C., Saravana Ram, R., Kouki, F., Alshahrani, H.M. and Assiri, M. (2023), "Analysis of barriers affecting Industry 4.0 implementation: An interpretive analysis using total interpretive structural modeling (TISM) and Fuzzy MICMAC", *Heliyon*, Vol. 9, No. 12, p. e22506, doi: 10.1016/j.heliyon.2023.e22506.
- Chen, C., Lee Kong, T. and Kan, W. (2023), "Identifying the promising production planning and scheduling method for manufacturing in Industry 4.0: a literature review", *Production &*

- Manufacturing Research*, Vol. 11, No. 1, p. 2279329, doi: 10.1080/21693277.2023.2279329.
- Cherapanukorn, V., Pattanasak, P. and Wudhikarn, R. (2025), "Key performance indicators for sustainable business incubation: identification and prioritization", *Sustainable Futures*, Vol. 10, p. 101284, doi: 10.1016/j.sftr.2025.101284.
- Crnjac, M., Veža, I. and Banduka, N. (2017), "From concept to the introduction of Industry 4.0", *International Journal of Industrial Engineering and Management*, Vol. 8, No. 1, pp. 21-30, doi: 10.24867/IJIEEM-2017-1-103.
- Ding, B., Ferrás-Hernández, X. and Agell, N. (2023), "Combining lean and agile manufacturing competitive advantages through Industry 4.0 technologies: an integrative approach", *Production Planning & Control*, Vol. 34, No. 5, pp. 442-458, doi: 10.1080/09537287.2021.1934587.
- Ebrahimi, S. and Bridgelall, R. (2021), "A fuzzy Delphi analytic hierarchy model to rank factors influencing public transit mode choice: A case study", *Research in Transportation Business & Management*, Vol. 39, p. 100496, doi: 10.1016/j.rtbm.2020.100496.
- Ghobakhloo, M. (2018), "The future of manufacturing industry: a strategic roadmap toward Industry 4.0", *Journal of Manufacturing Technology Management*, Vol. 29, No. 6, pp. 910-936, doi: 10.1108/jmtm-02-2018-0057.
- Habibi, A., Jahantigh, F.F. and Sarafrazi, A. (2015), "Fuzzy Delphi technique for forecasting and screening items", *Asian Journal of Research in Business Economics and Management*, Vol. 5, No. 2, pp. 130-143, doi: 10.5958/2249-7307.2015.00036.5.
- Hasan, M.A., Shankar, R. and Sarkis, J. (2007), "A study of barriers to agile manufacturing", *International Journal of Agile Systems and Management*, Vol. 2, No. 1, pp. 1-22, doi: 10.1504/IJASM.2007.015679.
- Horváth, D. and Szabó, R.Z. (2019), "Driving forces and barriers of Industry 4.0: Do multinational and small and medium-sized companies have equal opportunities?", *Technological Forecasting and Social Change*, Vol. 146, pp. 119-132, doi: 10.1016/j.techfore.2019.05.021.
- Hossain, S., Hassan, S. and Karim, R. (2023), "Assessment of Critical Barriers to Industry 4.0 Adoption in Manufacturing Industries of Bangladesh: An ISM-Based Study", *Brazilian Journal of Operations & Production Management*, Vol. 20, No. 3, p. 1797, doi: 10.14488/BJOPM.1797.2023.
- Hu, J.W.-S., Hu, Y.-C. and Tsai, A.C.-H. (2018), "Multiple criteria decision making and general regression for determining influential factors on S&P 500 index futures", *Symmetry*, Vol. 10, No. 1, p. 5, doi: 10.3390/sym10010005.
- Huang, J., Li, L., Jiang, P. and Zhang, S. (2024), "DEMATEL-Based ANP model for identifying critical indicators in sustainable emergency material reserve systems", *Sustainability*, Vol. 16, No. 12, p. 5263, doi: 10.3390/su16125263.
- Ivanov, D., Dolgui, A. and Sokolov, B. (2019), "The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics", *International Journal of Production Research*, Vol. 57, No. 3, pp. 829-846, doi: 10.1080/00207543.2018.1488086.
- Jadhav, J.R., Mantha, S.S. and Rane, S.B. (2014), "Barriers for successful implementation of JIT: a manufacturer perspective", *International Journal of Procurement Management*, Vol. 7, No. 3, pp. 316-342, doi: 10.1504/IJPM.2014.060790.
- Krishnamurthy, R. and Yauch, C.A. (2007), "Leagile manufacturing: a proposed corporate infrastructure", *International Journal of Operations & Production Management*, Vol. 27, No. 6, pp. 588-604, doi: 10.1108/01443570710750277.
- Kumar, R. and Kumar, V. (2014), "Barriers in implementation of lean manufacturing system in Indian industry: A survey", *International Journal of Latest Trends in Engineering and Technology*, Vol. 4, No. 2, pp. 243-251.
- Kuo, T.C., Hsu, C.-W. and Li, J.-Y. (2015), "Developing a green supplier selection model by using the DANP with VIKOR", *Sustainability*, Vol. 7, No. 2, pp. 1661-1689, doi: 10.3390/su7021661.
- Li, Y., Diabat, A. and Lu, C.-C. (2020), "Leagile supplier selection in Chinese textile industries: a DEMATEL approach", *Annals of Operations Research*, Vol. 287, No. 1, pp. 303-322, doi: 10.1007/s10479-019-03453-2.
- Liang, C., Sun, D. and Xie, D. (2023), "Identifying Waste Supply Chain Coordination Barriers with Fuzzy MCDM", *Sustainability*, Vol. 15, No. 6, p. 5352, doi: 10.3390/su15065352.
- Lin, Y.-H., Qiao, M. and Nwetlawung, Z.E. (2025), "A DANP model for evaluating the factors influencing blockchain adoption in the construction industry's carbon trading", *Urban Lifeline*, Vol. 3, p. 10, doi: 10.1007/s44285-025-00045-4.

- Minaee, M., Elahi, S., Majidpour, M. and Manteghi, M. (2021), "Lessons learned from an unsuccessful "catching-up" in the automobile industry of Iran", *Technology in Society*, Vol. 66, p. 101595, doi: 10.1016/j.techsoc.2021.101595.
- Mohaghegh, M. and Größler, A. (2025), "Leagile supply chains and sustainable business performance: application of total interpretive structural modelling", *Production Planning & Control*, Vol. 36, No. 8, pp. 1087-1109, doi: 10.1080/09537287.2024.2344063.
- Mohammadi, M., Elyasi, M. and Kiasari, M.M. (2014), "Developing a model for technological capability assessment — case of automotive parts manufacturers in Iran", *International Journal of Innovation and Technology Management*, Vol. 11, No. 2, p. 1450014, doi: 10.1142/s021987701450014x.
- Narkhede, B.E., Raut, R.D., Roy, M., Yadav, V.S. and Gardas, B. (2020), "Implementation barriers to lean-agile manufacturing systems for original equipment manufacturers: an integrated decision-making approach", *The International Journal of Advanced Manufacturing Technology*, Vol. 108, No. 9-10, pp. 3193-3206, doi: 10.1007/s00170-020-05486-5.
- Nawanir, G. and Moshood, T.D. (2025), "The drivers of lean, agile and green principles towards business competitiveness among manufacturing firms in Malaysia", *International Journal of Quality & Reliability Management*, Vol. 42, No. 6, pp. 1793-1821, doi: 10.1108/IJQRM-02-2024-0060.
- Nawaz, S. and Ali, Y. (2020), "Analyzing the influence of social, cultural, behavioral traits on cycling and walking in Pakistan", *Transportation Research Interdisciplinary Perspectives*, Vol. 7, p. 100182, doi: 10.1016/j.trip.2020.100182.
- Nordin, N., Md Deros, B. and Abd Wahab, D. (2010), "A survey on lean manufacturing implementation in Malaysian automotive industry", *International Journal of Innovation, Management and Technology*, Vol. 1, No. 4, pp. 374-380, doi: 10.7763/IJIMT.2010.V1.68.
- Núñez-Merino, M., Maqueira-Marín, J.M., Moyano-Fuentes, J. and Martínez-Jurado, P.J. (2020), "Information and digital technologies of Industry 4.0 and Lean supply chain management: a systematic literature review", *International Journal of Production Research*, Vol. 58, No. 16, pp. 5034-5061, doi: 10.1080/00207543.2020.1743896.
- Ojha, R. (2023), "Lean in Industry 4.0 is accelerating manufacturing excellence—A DEMATEL analysis", *The TQM Journal*, Vol. 35, No. 3, pp. 597-614, doi: 10.1108/TQM-11-2021-0318.
- Pereira, C.M., Anholon, R. and Batocchio, A. (2017), "Obstacles and difficulties implementing the lean philosophy in Brazilian enterprises", *Brazilian Journal of Operations & Production Management*, Vol. 14, No. 2, pp. 218-227, doi: 10.14488/BJOPM.2017.v14.n2.a10.
- Pereira, L. and Tortorella, G. (2018), "Identification of the relationships between critical success factors, barriers and practices for lean implementation in a small company", *Brazilian Journal of Operations & Production Management*, Vol. 15, No. 2, pp. 232-246, doi: 10.14488/BJOPM.2018.v15.n2.a6.
- Piotrowicz, W.D., Ryciuk, U. and Szymczak, M. (2023), "Lean and agile metrics. Literature review and framework for measuring leagile supply chain", *International Journal of Productivity and Performance Management*, Vol. 72, No. 6, pp. 1560-1583, doi: 10.1108/IJPPM-10-2020-0560.
- Potdar, P.K., Routroy, S. and Behera, A. (2017), "Analyzing the agile manufacturing barriers using fuzzy DEMATEL", *Benchmarking: An International Journal*, Vol. 24, No. 7, pp. 1912-1936, doi: 10.1108/bij-02-2016-0024.
- Rahiminezhad Galankashi, M. and Helmi, S.A. (2016), "Assessment of hybrid Lean-Agile (Leagile) supply chain strategies", *Journal of Manufacturing Technology Management*, Vol. 27, No. 4, pp. 470-482, doi: 10.1108/jmtm-08-2015-0069.
- Raj, A., Dwivedi, G., Sharma, A., Lopes De Sousa Jabbour, A.B. and Rajak, S. (2020), "Barriers to the adoption of industry 4.0 technologies in the manufacturing sector: An inter-country comparative perspective", *International Journal of Production Economics*, Vol. 224, p. 107546, doi: 10.1016/j.ijpe.2019.107546.
- Razmi, J., Hassani, A. and Babazadeh, R. (2015), "A hybrid fuzzy bi-objective delivery planning model for leagile e-tailing under uncertainty", *International Journal of Management Science and Engineering Management*, Vol. 10, No. 1, pp. 62-72, doi: 10.1080/17509653.2014.962110.
- Saad, S.M., Bahadori, R., Bhovar, C. and Zhang, H. (2024), "Industry 4.0 and lean manufacturing – a systematic review of the state-of-the-art literature and key recommendations for future research", *International Journal of Lean Six Sigma*, Vol. 15, No. 5, pp. 997-1024, doi: 10.1108/ijlss-02-2022-0021.

- Shahin, A. and Jaber, R. (2011), "Designing an integrative model of leagile production and analyzing its influence on the quality of auto parts based on Six Sigma approach with a case study in a manufacturing company", *International Journal of Lean Six Sigma*, Vol. 2, No. 3, pp. 215-240, doi: 10.1108/20401461111157187.
- Shen, K.-Y., Yan, M.-R. and Tzeng, G.-H. (2014), "Combining VIKOR-DANP model for glamor stock selection and stock performance improvement", *Knowledge-Based Systems*, Vol. 58, pp. 86-97, doi: 10.1016/j.knosys.2013.07.023.
- Si, S.-L., You, X.-Y., Liu, H.-C. and Zhang, P. (2018), "DEMATEL technique: a systematic review of the state-of-the-art literature on methodologies and applications", *Mathematical Problems in Engineering*, Vol. 2018, No. 1, p. 3696457, doi: 10.1155/2018/3696457.
- Silva, A.F., Veronese, G. and Matos, A.S. (2024), "Transforming the private label product development through the leagile paradigm", *Procedia Computer Science*, Vol. 232, pp. 1035-1044, doi: 10.1016/j.procs.2024.01.102.
- Sindhwani, R., Mittal, V.K., Singh, P.L., Aggarwal, A. and Gautam, N. (2019), "Modelling and analysis of barriers affecting the implementation of lean green agile manufacturing system (LGAMS)", *Benchmarking: An International Journal*, Vol. 26, No. 2, pp. 498-529, doi: 10.1108/bij-09-2017-0245.
- Singh, H. and Singh, B. (2024), "Industry 4.0 technologies integration with lean production tools: a review", *The TQM Journal*, Vol. 36, No. 8, pp. 2507-2526, doi: 10.1108/TQM-02-2022-0065.
- Srinivas, P., Gedam, V.V., Narkhede, B.E., Narwane, V.S. and Gotmare, A. (2022), "Sustainable implementation drivers and barriers of lean-agile manufacturing in original equipment manufacturers: a literature review study", *International Journal of Business Excellence*, Vol. 26, No. 1, pp. 61-94, doi: 10.1504/IJBEX.2022.121587.
- Sun, D., Guo, D. and Xie, D. (2023), "Using multicriteria decision making to evaluate the risk of hydrogen energy storage and transportation in cities", *Sustainability*, Vol. 15, No. 2, p. 1088, doi: 10.3390/su15021088.
- Sutrisno, S., Suef, M. and Ma'ruf, B. (2024), "A conceptual model of agile manufacturing in the shipbuilding industry for improving shipyard performance", *International Journal of Agile Systems and Management*, Vol. 17, No. 2, pp. 246-268, doi: 10.1504/IJASM.2024.138863.
- Torre, N., Leo, C. and Bonamigo, A. (2023), "Lean 4.0: An analytical approach for hydraulic system maintenance in a production line of a steel-making plant", *International Journal of Industrial Engineering and Management*, Vol. 14, No. 3, pp. 186-199, doi: 10.24867/IJIEEM-2023-3-332.
- Upadhyay, A. and Shukla, A.C. (2025), "Identifying and prioritizing barriers to circular supply chain management in Indian micro, small, & medium enterprises: A DANP-based approach", *Business Strategy & Development*, Vol. 8, No. 3, p. e70183, doi: 10.1002/bsd2.70183.
- Upadhye, N., Deshmukh, S. and Garg, S. (2016), "Lean manufacturing system implementation barriers: an interpretive structural modelling approach", *International Journal of Lean Enterprise Research*, Vol. 2, No. 1, pp. 46-65, doi: 10.1504/IJLER.2016.078232.
- Urquia, I., Amrani, A.Z. and Vallespir, B. (2025), "A method to support joint integration of Lean manufacturing and Industry 4.0", *The International Journal of Advanced Manufacturing Technology*, Vol. 136, No. 5-6, pp. 2305-2323, doi: 10.1007/s00170-024-14914-9.
- Virmani, N., Saha, R. and Sahai, R. (2017), "Understanding the barriers in implementing leagile manufacturing system", *International Journal of Productivity and Quality Management*, Vol. 22, No. 4, pp. 499-520, doi: 10.1504/IJPQM.2017.087866.
- Virmani, N., Saha, R. and Sahai, R. (2018), "Empirical assessment of critical success factors of leagile manufacturing using fuzzy DEMATEL approach", *International Journal of Agile Systems and Management*, Vol. 11, No. 4, pp. 293-314, doi: 10.1504/IJASM.2018.095511.
- Wu, C.-H. and Fang, W.-C. (2011), "Combining the Fuzzy Analytic Hierarchy Process and the fuzzy Delphi method for developing critical competences of electronic commerce professional managers", *Quality & Quantity*, Vol. 45, No. 4, pp. 751-768, doi: 10.1007/s11135-010-9425-6

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APPENDIX A

Table A1 - Direct influence matrix (A)

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11
B1	0.00	3.60	2.73	2.33	2.00	1.80	2.47	3.07	2.40	3.27	3.73
B2	2.13	0.00	2.00	2.40	1.60	1.67	3.13	3.40	0.67	2.60	1.60
B3	1.13	1.53	0.00	2.20	2.73	2.67	2.00	1.93	3.80	2.20	2.60
B4	2.73	2.07	1.93	0.00	3.07	2.80	2.53	1.40	1.47	3.07	2.53
B5	2.87	3.20	2.47	3.40	0.00	3.20	2.07	2.60	2.87	3.00	2.67
B6	2.67	2.33	2.40	3.47	3.27	0.00	2.33	1.60	1.80	2.13	2.13
B7	1.60	2.00	2.27	2.47	2.67	2.40	0.00	2.87	1.13	2.80	1.93
B8	2.27	2.60	2.33	2.33	2.73	1.93	3.47	0.00	0.93	2.67	2.20
B9	1.80	1.73	3.60	2.20	2.33	1.47	2.13	1.47	0.00	3.33	3.07
B10	2.07	2.20	3.33	2.47	1.60	1.33	2.53	1.67	2.47	0.00	1.73
B11	2.40	2.93	2.67	2.80	3.33	2.60	2.13	2.07	3.13	2.40	0.00

Source: The author himself.

Table A2 - Normalized direct influence matrix (D)

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11
B1	0.000	0.127	0.096	0.082	0.071	0.063	0.087	0.108	0.085	0.115	0.132
B2	0.075	0.000	0.071	0.085	0.056	0.059	0.110	0.120	0.024	0.092	0.056
B3	0.040	0.054	0.000	0.078	0.096	0.094	0.071	0.068	0.134	0.078	0.092
B4	0.096	0.073	0.068	0.000	0.108	0.099	0.089	0.049	0.052	0.108	0.089
B5	0.101	0.113	0.087	0.120	0.000	0.113	0.073	0.092	0.101	0.106	0.094
B6	0.094	0.082	0.085	0.122	0.115	0.000	0.082	0.056	0.063	0.075	0.075
B7	0.056	0.071	0.080	0.087	0.094	0.085	0.000	0.101	0.040	0.099	0.068
B8	0.080	0.092	0.082	0.082	0.096	0.068	0.122	0.000	0.033	0.094	0.078
B9	0.063	0.061	0.127	0.078	0.082	0.052	0.075	0.052	0.000	0.117	0.108
B10	0.073	0.078	0.117	0.087	0.056	0.047	0.089	0.059	0.087	0.000	0.061
B11	0.085	0.103	0.094	0.099	0.117	0.092	0.075	0.073	0.110	0.085	0.000

Source: The author himself.

Table A3 - DANP weighted supermatrix

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11
B1	0.088	0.108	0.103	0.100	0.099	0.099	0.102	0.107	0.104	0.104	0.109
B2	0.083	0.069	0.080	0.082	0.078	0.080	0.087	0.091	0.073	0.082	0.078
B3	0.082	0.084	0.075	0.087	0.090	0.092	0.086	0.086	0.100	0.086	0.090
B4	0.095	0.090	0.088	0.078	0.094	0.095	0.092	0.087	0.088	0.093	0.092
B5	0.110	0.109	0.105	0.109	0.091	0.111	0.103	0.107	0.110	0.106	0.107
B6	0.097	0.093	0.092	0.098	0.097	0.079	0.092	0.090	0.092	0.090	0.092
B7	0.083	0.084	0.085	0.086	0.087	0.088	0.072	0.090	0.080	0.087	0.084
B8	0.091	0.092	0.089	0.089	0.091	0.089	0.096	0.077	0.083	0.090	0.089
B9	0.087	0.085	0.095	0.087	0.088	0.085	0.087	0.085	0.076	0.092	0.093
B10	0.083	0.082	0.088	0.083	0.079	0.079	0.084	0.081	0.087	0.070	0.080

B11	0.101	0.103	0.100	0.101	0.104	0.102	0.098	0.099	0.107	0.098	0.086
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Source: The author himself.

Table A4 - DANP limit supermatrix

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11
B1	0.1019	0.1019	0.1019	0.1019	0.1019	0.1019	0.1019	0.1019	0.1019	0.1019	0.1019
B2	0.0804	0.0804	0.0804	0.0804	0.0804	0.0804	0.0804	0.0804	0.0804	0.0804	0.0804
B3	0.0872	0.0872	0.0872	0.0872	0.0872	0.0872	0.0872	0.0872	0.0872	0.0872	0.0872
B4	0.0904	0.0904	0.0904	0.0904	0.0904	0.0904	0.0904	0.0904	0.0904	0.0904	0.0904
B5	0.1060	0.1060	0.1060	0.1060	0.1060	0.1060	0.1060	0.1060	0.1060	0.1060	0.1060
B6	0.0921	0.0921	0.0921	0.0921	0.0921	0.0921	0.0921	0.0921	0.0921	0.0921	0.0921
B7	0.0844	0.0844	0.0844	0.0844	0.0844	0.0844	0.0844	0.0844	0.0844	0.0844	0.0844
B8	0.0888	0.0888	0.0888	0.0888	0.0888	0.0888	0.0888	0.0888	0.0888	0.0888	0.0888
B9	0.0876	0.0876	0.0876	0.0876	0.0876	0.0876	0.0876	0.0876	0.0876	0.0876	0.0876
B10	0.0813	0.0813	0.0813	0.0813	0.0813	0.0813	0.0813	0.0813	0.0813	0.0813	0.0813
B11	0.0999	0.0999	0.0999	0.0999	0.0999	0.0999	0.0999	0.0999	0.0999	0.0999	0.0999

Source: The author himself.

Table A5 - Candidate barriers and representative literature sources

Candidate code	Candidate barrier	Representative source(s)	Final Delphi outcome	Final retained code
C1	Lack of employee training	Jadhav et al. (2014); Sindhvani et al. (2019)	Retained	B1
C2	Inadequate use of employee empowerment	Virmani et al. (2017)	Retained	B2
C3	Lack of a clear system vision	Kumar and Kumar (2014); Srinivas et al. (2022)	Rejected	—
C4	Lack of information technology facilities	Ben Ruben et al. (2023); Potdar et al. (2017)	Rejected	—
C5	Lack of supplier integration	Hasan et al. (2007); Virmani et al. (2017)	Rejected	—
C6	Lack of interpersonal skills	Virmani et al. (2017)	Rejected	—
C7	Communication gap	Kumar and Kumar (2014); Sindhvani et al. (2019)	Rejected	—
C8	Lack of advanced production facilities	Virmani et al. (2017); Potdar et al. (2017)	Rejected	—
C9	Lack of continuous improvement culture	Virmani et al. (2017); Srinivas et al. (2022)	Rejected	—
C10	Lack of benchmarking and standardization	Virmani et al. (2017); Srinivas et al. (2022)	Retained	B3
C11	Poor planning	Potdar et al. (2017); Sindhvani et al. (2019)	Retained	B4
C12	Process inefficiency	Potdar et al. (2017); Srinivas et al. (2022)	Rejected	—
C13	Insufficient time for change and transformation	Kumar and Kumar (2014); Virmani et al. (2017)	Rejected	—
C14	Weak reward and recognition system	Hasan et al. (2007); Srinivas et al. (2022)	Rejected	—
C15	Lack of training budget	Virmani et al. (2017)	Rejected	—

C16	Lack of top management commitment	Hasan et al. (2007); Jadhav et al. (2014)	Retained	B6
C17	Lack of flexibility	Hasan et al. (2007); Potdar et al. (2017)	Retained	B7
C18	Employee resistance to change	Sindhwani et al. (2019); Pereira and Tortorella (2018)	Retained	B8
C19	Absence of an appropriate leagile performance measurement system	Narkhede et al. (2020); Srinivas et al. (2022)	Retained	B9
C20	Weak implementation of improvement programs (e.g., TQM, JIT, ERP, and TPM)	Narkhede et al. (2020); Kumar and Kumar (2014)	Rejected	—
C21	Weak communication and cooperation among managerial levels and employees	Narkhede et al. (2020); Srinivas et al. (2022)	Rejected	—
C22	Inadequate incentive and compensation systems	Narkhede et al. (2020); Srinivas et al. (2022)	Rejected	—
C23	Lack of technological upgrading and innovation	Narkhede et al. (2020); Srinivas et al. (2022)	Retained	B10
C24	Lack of understanding of sustainable products and production	Narkhede et al. (2020); Srinivas et al. (2022)	Rejected	—
C25	Weak supplier–customer cooperation	Narkhede et al. (2020)	Rejected	—
C26	Initial capital and budget constraints	Narkhede et al. (2020); Pereira et al. (2017)	Rejected	—
C27	Lack of attention to technological compatibility and regulatory requirements	Raj et al. (2020); Ben Ruben et al. (2023)	Rejected	—
C28	Ineffective organizational management	Narkhede et al. (2020)	Retained	B5
C29	Lack of understanding of leagile concepts	Expert-suggested	Retained	B11
C30	Imbalance between supply and demand	Expert-suggested	Rejected	—
C31	Lack of required technical knowledge and skills	Expert-suggested	Rejected	—

Source: The author himself.

Table A6 - Fuzzy Delphi threshold sensitivity

Cutoff threshold (τ)	Number of retained barriers	Final retained barrier codes	Exclusions relative to the baseline
0.700	11	B1, B2, B3, B4, B5, B6, B7, B8, B9, B10, B11	None
0.725	11	B1, B2, B3, B4, B5, B6, B7, B8, B9, B10, B11	None
0.750	7	B1, B2, B4, B5, B6, B9, B11	B3 (0.728), B7 (0.739), B8 (0.734), B10 (0.734)

Source: The author himself.

Note: Alternative cutoffs were applied to the unrounded Round 3 crisp scores. Values reported in Table 4 and this table are rounded to three decimal places. Items with $DF_i \geq \tau$ were retained. DEMATEL–DANP was not re-estimated under the alternative cutoffs.