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Needs Assessment and Clustering of Technological Infrastructure for the Transition to Industry 4.0 and Industry 5.0 in Small and Medium-Sized Enterprises: A Systematic Literature Review and Computational Text Analysis Approach

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Abstract

In the current global business landscape, organizations face increasing pressure to align with technological advancements. Small and medium-sized enterprises (SMEs), as key drivers of economic growth, must enhance their absorptive capacities to maintain competitiveness within digital ecosystems. However, while Industry 4.0 primarily focuses on industrial optimization, Industry 5.0 introduces a new paradigm emphasizing social values and human-centricity. Many SMEs encounter significant challenges in this transition due to the complexities of adopting smart manufacturing and the lack of appropriate maturity assessment frameworks. To address existing gaps in the literature, the present study aims to identify and cluster the infrastructural dimensions and criteria required for transitioning to Industry 4.0 and Industry 5.0. This study employs an integrated methodological approach combining a systematic literature review (SLR) with computational text analysis. The research process involves systematic database searches, multistage screening, and data extraction based on a transparent protocol. Subsequently, to refine the extracted data and identify latent patterns, natural language processing and computational techniques were employed, including Sentence-BERT (SBERT) for semantic representation, k-nearest neighbors (k-NN) for neighborhood analysis, the Leiden algorithm for clustering, and PaCMAP for visualization. The findings indicate that the initial dataset, comprising 572 features, was ultimately reduced to 49 key indicators classified into seven final clusters. These indicators provide a practical framework for assessing technological readiness and facilitating the strategic transition of SMEs toward emerging industrial paradigms.

Keywords: Industry 4.0, Industry 5.0, small and medium-sized enterprises (SMEs), systematic literature review, computational text analysis.

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1. Introduction

The accelerating diffusion of digital technologies has fundamentally transformed the competitive environment of manufacturing organizations and has redefined the technological, organizational, and strategic requirements of industrial development. Over the past decade, Industry 4.0 has emerged as a dominant paradigm for integrating digital technologies, intelligent automation, interconnected production systems, and data-driven decision-making into manufacturing operations. Technologies such as the Internet of Things (IoT), cyber-physical systems (CPS), cloud computing, artificial intelligence, big data analytics, advanced robotics, and digital platforms increasingly enable firms to improve productivity, flexibility, quality, visibility, and operational responsiveness. For small and medium-sized enterprises (SMEs), however, adopting these technologies is not merely a matter of purchasing new technological assets; it requires the coordinated development of digital infrastructure, organizational capabilities, human competencies, financial resources, managerial commitment, and strategic alignment (Karuppiah et al., 2023; Kee et al., 2025; Marcon et al., 2022; Pandey et al., 2024).

SMEs occupy a particularly important position within industrial ecosystems because of their contribution to employment, entrepreneurship, supply networks, regional development, and economic adaptability. At the same time, they generally operate under more restrictive conditions than large enterprises, including limited capital availability, shortages of specialized technological expertise, lower levels of formalization, weaker digital infrastructure, and greater sensitivity to investment risks. Consequently, the transition toward Industry 4.0 can place substantial pressure on SMEs that must simultaneously maintain short-term operational performance and invest in long-term technological transformation. Empirical evidence suggests that barriers to digitalization in SMEs extend beyond technological deficiencies and include financial constraints, resistance to change, workforce capability gaps, uncertainty regarding return on investment, lack of strategic roadmaps, and insufficient managerial knowledge (Hansen et al., 2025; Ingaldi & Ulewicz, 2025; Kumar et al., 2025). These challenges indicate that technological readiness should be conceptualized as a multidimensional organizational condition rather than as the simple availability of digital technologies.

The implementation of Industry 4.0 technologies within SMEs therefore depends on the simultaneous development of technical and nontechnical enablers. Studies examining SME readiness have identified management support, strategic planning, technological infrastructure, workforce competence, organizational culture, external collaboration, financial readiness, and innovation capability as major determinants of successful digital transformation (Karuppiah et al., 2023; Kee et al., 2025). In particular, IoT implementation requires not only sensors, communication networks, and data platforms but also interoperability standards, cybersecurity provisions, qualified personnel, and appropriate implementation frameworks (Abdulaziz et al., 2023). Similarly, the assessment of Industry 4.0 readiness increasingly requires practical evaluation of industrial IoT architectures, sensing systems, connectivity, and network performance because weaknesses in these foundational layers can constrain the effectiveness of more advanced digital applications (Anbalagan et al., 2024). Therefore, identifying the infrastructural requirements of digital transformation is an essential prerequisite for designing realistic transition pathways for SMEs.

The growing importance of sustainability has further expanded the scope of Industry 4.0 implementation. Digital transformation is increasingly expected to contribute not only to operational efficiency but also to environmental performance, resource productivity, social responsibility, and long-term business resilience. Digital technologies can support energy management, waste reduction, traceability, predictive maintenance, optimized logistics, and sustainable supply-chain coordination; however, their sustainability outcomes are neither automatic nor uniformly positive (Jamwal et al., 2025; Kunkel et al., 2022). In supply-chain contexts, Industry 4.0 technologies may facilitate collaboration, information transparency, and resource efficiency, but the benefits depend on organizational coordination and the capacity of supply-chain partners to absorb and use digital information effectively (Kunkel et al., 2022). Likewise, Industry 4.0 can strengthen sustainable and leagile supplier selection by enabling more sophisticated evaluation and decision-support mechanisms (ForouzeshNejad, 2023). These findings emphasize that digital infrastructure must be evaluated in relation to broader operational and sustainability systems rather than as an isolated technological domain.

At the same time, concerns have emerged regarding the potential negative consequences of Industry 4.0. Excessive technological orientation, poorly designed automation, digital inequality, employee displacement, intensified work demands,

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privacy risks, and environmental rebound effects may undermine the economic, environmental, and social dimensions of sustainability (Narkhede, Chinchanikar, et al., 2024). Such concerns have contributed to the development of Industry 5.0, which extends the Industry 4.0 paradigm by emphasizing human-centricity, resilience, and sustainability. Rather than replacing Industry 4.0, Industry 5.0 can be understood as an evolution that seeks to integrate technological sophistication with social and human values (Islam et al., 2025; Martín-Gómez et al., 2024). Within this emerging paradigm, industrial technologies are expected to augment rather than merely substitute human capabilities, and manufacturing systems are increasingly evaluated according to their capacity to generate economic value while simultaneously supporting worker well-being, environmental sustainability, and systemic resilience.

The transition from Industry 4.0 to Industry 5.0 therefore involves a broader reconfiguration of organizational priorities. Human–machine collaboration becomes a central design principle, requiring firms to reconsider the relationships among automation, employee autonomy, digital competencies, occupational roles, decision authority, and workplace design (Islam et al., 2025). Human-centric manufacturing places workers at the center of technological transformation and requires systems that are adaptable to human needs, capabilities, and limitations. In SMEs, however, implementing human-centric manufacturing is particularly difficult because limited resources, insufficient knowledge, uncertainty regarding technological solutions, and weak institutional support can restrict adoption (Zare et al., 2025). Requirements for human-centered SMEs consequently include employee involvement, ergonomic and socially responsible technology design, continuous competence development, organizational flexibility, and supportive leadership structures (Nazarejova et al., 2024).

Human-centricity also introduces new technological possibilities. Human digital twins, for example, provide a means of representing human characteristics, behaviors, and interactions within digitally integrated production environments, thereby supporting more adaptive and worker-centered industrial systems (Modoni & Sacco, 2023). Nevertheless, the effective use of such technologies depends on the existence of foundational organizational and digital capabilities. Firms cannot meaningfully adopt sophisticated human-centric technologies without adequate data infrastructure, interoperability, workforce skills, governance mechanisms, and strategic coordination. Consequently, the technological transition toward Industry 5.0 should be approached as a staged capability-building process rather than as an isolated technological upgrade.

The sustainability and resilience dimensions of Industry 5.0 similarly require systemic thinking. Industry 5.0 supply chains are increasingly conceptualized as systems that combine digital intelligence with sustainability, human-centricity, and resilience in order to respond more effectively to disruptions and changing stakeholder expectations (Dacre et al., 2025). In emerging economies, the diffusion of Industry 5.0 practices within SME supply chains depends on multiple interrelated enablers, including digital technologies, organizational learning, collaborative structures, policy support, and sustainability-oriented management (Hsu et al., 2024). Likewise, Industry 5.0 is increasingly discussed as a framework for advancing sustainable manufacturing by integrating technological capability with circularity, social responsibility, resilient systems, and stakeholder-oriented value creation (Narkhede, Dohale, et al., 2024). These developments suggest that assessments of SME readiness must move beyond narrow measures of automation or digitization and incorporate technological, organizational, human, strategic, and sustainability-oriented infrastructures.

The connection between digitalization and sustainable business model innovation further reinforces this multidimensional perspective. Sustainable transformation requires organizations to redesign value propositions, value creation processes, partnerships, resource configurations, and stakeholder relationships rather than merely introduce new technological tools. Research on sustainable business model innovation has identified organizational resistance, uncertainty, institutional pressures, market conditions, stakeholder engagement, leadership, and resource availability as important drivers and barriers (Hansson et al., 2023; Sampene et al., 2023). Therefore, digital transformation in SMEs should be understood within the wider context of business model adaptation and organizational change, particularly because SMEs often lack the slack resources available to larger corporations.

Lean management and operational excellence represent another important dimension of the transition to advanced industrial systems. The convergence of Industry 4.0 with lean production can improve process visibility, waste reduction, responsiveness, quality, and continuous improvement; however, technological implementation without appropriate operational foundations may fail to generate the expected benefits. Integrating Lean Six Sigma with Industry 4.0 requires critical success factors such

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as management commitment, employee participation, training, digital competence, organizational culture, data-driven decision-making, and adequate infrastructure (Samanta et al., 2023). Similarly, the integration of operational excellence strategies with Industry 4.0 technologies in manufacturing SMEs is affected by financial limitations, technological complexity, workforce readiness, organizational resistance, and inadequate strategic planning (Joshi et al., 2024). The integration of lean, green, and Industry 4.0 practices also depends on coordinated stakeholder involvement and organizational drivers that facilitate collaborative implementation (Zhu et al., 2022). These findings indicate that technological readiness is inseparable from process management, organizational routines, and continuous-improvement capabilities.

Human resource management is particularly important because digital transformation alters both the technical content of work and the competencies required to perform it. SMEs frequently encounter shortages of employees capable of operating, interpreting, maintaining, and improving digital systems. Human resource barriers include inadequate digital skills, fear of technological displacement, insufficient training, lack of interdisciplinary competencies, resistance to organizational change, and limited understanding of Industry 4.0 requirements (Sharma et al., 2022). The progression toward Industry 5.0 further intensifies the need for upskilling and reskilling because employees must increasingly interact with intelligent systems while simultaneously exercising judgment, creativity, problem-solving, collaboration, and ethical responsibility. Educational support and structured learning initiatives can therefore play a critical role in enabling SMEs to move from Industry 4.0 toward Industry 5.0 (Solvang et al., 2024).

Moreover, the development of viable transition pathways requires a strategic understanding of how new technologies can be adopted incrementally and sustainably. SMEs generally cannot implement all advanced technologies simultaneously, making prioritization essential. Models designed to support the adoption of technologies across Industry 4.0 and Industry 5.0 emphasize the importance of aligning technological choices with organizational viability, sustainability objectives, operational requirements, and available capabilities (Solano García et al., 2025). This need for prioritization is especially important because digital transformation investments can involve substantial uncertainty and because technologies that are appropriate for one SME may not be suitable for another. A structured readiness framework can help firms identify capability gaps, sequence investments, and avoid technology adoption driven primarily by trends rather than strategic necessity.

Despite the expanding body of research on Industry 4.0 and Industry 5.0, the literature remains fragmented across technological, organizational, human, operational, and sustainability domains. Some studies focus primarily on technological adoption factors, whereas others emphasize human resource readiness, sustainability, lean management, supply chains, or business models. As a result, there remains a need for an integrated synthesis capable of identifying and organizing the infrastructural indicators that recur across these different streams of research. This fragmentation is particularly problematic for SMEs because managers require concise and actionable frameworks rather than disconnected lists of technological and organizational factors.

Systematic literature review methods provide an appropriate basis for consolidating this fragmented knowledge, but conventional manual synthesis may remain vulnerable to interpretive inconsistency when large numbers of conceptually similar indicators are extracted. Computational text analysis provides complementary tools for identifying semantic relationships among textual indicators and reducing redundancy. Sentence-embedding approaches are particularly useful because they represent short textual expressions in a continuous semantic vector space, allowing conceptually similar phrases to be detected even when they use different vocabulary (Rabiei Zadeh & Amirkhani, 2023). Sentence-BERT-based representations have been successfully applied in tasks requiring identification of semantic similarity and duplicate or near-duplicate textual items (Isotani et al., 2023). Studies of SBERT have also demonstrated the importance of model architecture and pooling strategies in improving short-text clustering and semantic representation (Ortakci, 2024). These capabilities make sentence embeddings suitable for consolidating indicators extracted from heterogeneous academic studies.

Graph-based techniques provide an additional analytical layer by transforming pairwise semantic similarities into networks in which conceptually related indicators can be represented as neighboring nodes. Pre-trained contextual embeddings combined with graph-based blocking and matching methods have shown considerable potential for identifying related entities in complex textual datasets (Mugeni & Amagasa, 2022). More broadly, graph-based clustering approaches are effective for handling high-dimensional data because they preserve local relational structures and enable the identification of communities or clusters

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within complex data spaces (Li et al., 2023). Community-detection algorithms such as the Leiden algorithm are particularly suitable for identifying densely connected regions within similarity graphs and have been applied successfully to complex network-analysis problems (Sihombing et al., 2025).

Dimensionality-reduction techniques can further improve the interpretability of such high-dimensional semantic structures. PaCMAP is designed to preserve local, intermediate, and global relationships when mapping high-dimensional data into lower-dimensional spaces, making it useful for identifying visually interpretable groupings within complex datasets (Qattous et al., 2024). When integrated with semantic embeddings and graph-based clustering, dimensionality reduction can support a more transparent examination of conceptual proximity among indicators and help distinguish coherent thematic domains. Such computational approaches are therefore particularly relevant for systematic reviews seeking to move beyond descriptive aggregation toward reproducible and data-driven conceptual synthesis.

The need for an integrated approach is reinforced by the increasingly complex relationship between technological advancement and sustainable manufacturing. Sustainable manufacturing frameworks increasingly combine Industry 4.0 technologies with Industry 5.0 values, illustrating that future industrial competitiveness will depend on the simultaneous integration of digital efficiency, environmental sustainability, human-centricity, and resilience (Martín-Gómez et al., 2024). Practical frameworks for sustainable manufacturing likewise emphasize coordinated technological, organizational, environmental, and human interventions (Riosvelasco-Monroy et al., 2022). Accordingly, readiness assessment for SMEs should not be limited to isolated technological assets, but should identify the interconnected infrastructural dimensions that enable firms to progress toward both Industry 4.0 and Industry 5.0.

Against this background, the aim of the present study is to systematically identify, consolidate, and cluster the technological, organizational, human, strategic, and sustainability-related infrastructural indicators required for SMEs to transition toward Industry 4.0 and Industry 5.0 by integrating a systematic literature review with computational semantic analysis, graph-based clustering, and dimensionality-reduction techniques.

2. Methods and Materials

The present study employed a systematic literature review (SLR) to identify a comprehensive set of infrastructural indicators required for transitioning to Industry 4.0 and Industry 5.0. Accordingly, an extensive search was conducted in the Scopus and Web of Science databases, and all retrieved records were screened using a three-stage protocol involving title, abstract, and full-text screening. This rigorous process ensured that only studies with substantial relevant content and alignment with the research objectives were included in the data extraction process. Following the identification of eligible articles, key concepts and technological requirements were extracted and categorized using MAXQDA 20 software.

To enhance analytical accuracy and minimize subjective biases associated with manual coding, an advanced computational pipeline was implemented. First, the extracted indicators were transformed into semantic vectors (embeddings) using the Sentence-BERT (SBERT) model to represent conceptual relationships among textual elements in a multidimensional space. Subsequently, a k-nearest neighbors (k-NN) graph was constructed to model the relationships among these indicators. By calculating cosine similarity, this graph established weighted edges that captured both the locality of semantic neighborhoods and the strength of pairwise relationships among indicators, thereby providing the underlying structure of the data space for clustering.

In the next stage, the Leiden algorithm was employed for graph-based community detection and clustering. By optimizing modularity, this algorithm identified communities (clusters) characterized by high internal cohesion and well-defined boundaries. For visual interpretation and a better understanding of the cluster structure, Pairwise Controlled Manifold Approximation and Projection (PaCMAP) was used to reduce the high-dimensional data to a two-dimensional space while preserving local, intermediate, and distant relationships among data points. The integration of these two methods preserved the fine-grained semantic structure derived from SBERT, reinforced the boundaries of the structural clusters, and produced interpretable and well-supported outputs for final validation.

In the final stage, a minimum occurrence threshold of two was applied to enhance the robustness and generalizability of the findings. Accordingly, only indicators reported in at least two independent studies were retained. The exclusion of indicators

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appearing only once did not imply that they were unimportant; rather, it was intended to filter out case-specific findings and emphasize concepts supported by the broader literature and conceptual consensus. This data-driven and reproducible approach reduced the final set to 49 established indicators, providing a reliable foundation for specialized analyses and assessments of SME readiness.

3. Findings and Results

Systematic searches were conducted in the Scopus and Web of Science (WoS) databases using the relevant key concepts and search specifications presented in Table 1.

Table 1. Database Search Strategies, Keywords, and Eligibility Restrictions

Key Concepts and Search Strings	Database	Search Conditions
("Small and Medium Enterprises" OR "SMEs") AND ("Industry 4.0" OR "Industry4.0") AND ("Sustainability" OR "Resilience" OR "Human resource management" OR "Human-centricity")	Scopus	Search fields: Article title, abstract, and keywords. Document type: Article. Language: English.
("Small and Medium Enterprises" OR "SMEs") AND ("Industry 5.0" OR "Industry5.0") AND ("Sustainability" OR "Resilience" OR "Human resource management" OR "Human-centricity")	Scopus	Search fields: Article title, abstract, and keywords. Document type: Article. Language: English.
("Small and Medium Enterprises" OR "SMEs") AND ("Industry 4.0" OR "Industry4.0") AND ("Sustainability" OR "Resilience" OR "Human resource management" OR "Human-centricity")	Web of Science (WoS)	Search fields: All fields. Document type: Article. Language: English.
("Small and Medium Enterprises" OR "SMEs") AND ("Industry 5.0" OR "Industry5.0") AND ("Sustainability" OR "Resilience" OR "Human resource management" OR "Human-centricity")	Web of Science (WoS)	Search fields: All fields. Document type: Article. Language: English.

Among the records retrieved from these two databases, only English-language journal articles classified as "Article" were retained. The keyword searches related to Industry 4.0 yielded 116 articles in Scopus and 232 articles in WoS. Similarly, the searches related to Industry 5.0 identified 38 articles in Scopus and 19 articles in WoS. However, a considerable number of records were duplicated across the searches. Following duplicate removal, 252 articles related to Industry 4.0 and 32 articles related to Industry 5.0 were retained from the two databases.

Of the 252 articles related to Industry 4.0, 31 were classified as directly relevant (Category A), 141 as potentially relevant or ambiguous (Category B), requiring further screening, and 80 as irrelevant or outside the scope of the study (Category C). Similarly, among the 32 articles related to Industry 5.0, three were classified as Category A, 21 as Category B, and eight as Category C. Accordingly, a total of 162 articles (141 + 21) proceeded to the abstract-screening stage.

Among the 141 Industry 4.0 articles assessed during abstract screening, 12 were classified as Category A, 56 as Category B, and 73 as Category C. Likewise, among the 21 Industry 5.0 articles, two, eight, and 11 were assigned to Categories A, B, and C, respectively. For the subsequent screening stage, the full texts of all 64 articles classified as Category B were selected for further assessment.

Following the full-text assessment of the articles retained from the preceding screening stage, 18 of the 56 Industry 4.0 articles were selected, while the remaining 38 were excluded. Of the eight Industry 5.0 articles, only one was retained, and the remaining seven were excluded. Thus, 19 eligible articles were identified and selected at this stage. Overall, as presented in Table 2, the three-stage screening process yielded a final sample of 67 articles.

Table 2. Results of the Three-Stage Screening Process for Industry 4.0 and Industry 5.0 Articles

	Industry 4.0			Industry 5.0		
Category	Title Screening	Abstract Screening	Full-Text Screening	Title Screening	Abstract Screening	Full-Text Screening
A	31	12	18	3	2	1
B	141	56	—	21	8	—
C	80	73	38	8	11	7

At this stage, detailed data extraction was performed for all studies included after the screening process (67 articles) using MAXQDA 20 software. This procedure yielded a total of 695 indicators.

All 695 extracted indicators were encoded into dense semantic representations using Sentence-BERT. In this study, Sentence-BERT was employed to transform each indicator extracted from the articles into a numerical semantic vector, enabling the calculation of conceptual similarity between indicators even when their linguistic expressions differed. Using the

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all-MiniLM-L6-v2 model, each indicator was mapped onto a 384-dimensional semantic vector, allowing contextual similarity to be analyzed beyond superficial lexical overlap. The dimensionality of 384 is specific to the architecture of the all-MiniLM-L6-v2 model. Compared with larger models, this lightweight model offers greater computational efficiency while maintaining high accuracy in sentence-level semantic similarity estimation and generating a relatively low-noise embedding space. This semantic encoding established the foundation for subsequent similarity modeling and graph-based clustering.

To model semantic relationships among the indicators, a k-nearest neighbors (k-NN) similarity graph was constructed using cosine similarity. This similarity graph-based approach is widely used to represent semantic structures in vectorized data because it preserves local structures while controlling overall network connectivity. Within this framework, selecting an appropriate value of k is particularly important, as smaller values can lead to network fragmentation, whereas larger values may cause structural oversmoothing and the loss of local distinctions. Based on recommendations in the existing literature, intermediate values (approximately 10–30 neighbors) provide an appropriate balance between cohesion and discriminability. Accordingly, k = 15 was selected as an intermediate and theoretically defensible value.

Furthermore, an empirical analysis was conducted across a broad range of similarity thresholds while keeping the neighborhood size fixed at different candidate values. This procedure enabled an examination of the network structure's sensitivity to variations in the similarity threshold and helped avoid arbitrary parameter selection. For the selected value of k = 15, the resulting connectivity patterns demonstrated a desirable balance between sparsity and structural cohesion. An examination of graph statistics across different threshold levels, as presented in Table 3, showed that at higher similarity thresholds (e.g., 0.90–0.95), most nodes remained isolated or formed only trivial components, indicating insufficient neighborhood density. This finding suggests that these thresholds were excessively restrictive, eliminating potentially meaningful semantic relationships and thereby reducing the network's ability to represent conceptual domains.

As the similarity threshold decreased, meaningful semantic clusters began to emerge. At a threshold of 0.75, the graph exhibited a desirable structure: the number of connected components decreased substantially (580 components), the largest community became sufficiently large to represent a coherent semantic region (12 nodes), and the number of isolated nodes decreased considerably compared with higher thresholds (from 672 at 0.95 to 518 at 0.75). Therefore, selecting a threshold of 0.75 not only reduced node isolation and increased network cohesion from a structural perspective but also enabled the preservation of high-confidence conceptual relationships from a semantic perspective.

Table 3. Sensitivity Analysis of k-Nearest Neighbors Graph Structure Across Cosine Similarity Thresholds (k = 15)

Similarity Threshold	Clusters	Mean Cluster Size	Median Cluster Size	Largest Cluster	Isolated Nodes
0.95	683	1.017570	1.0	3	672
0.90	675	1.029630	1.0	4	658
0.88	672	1.034226	1.0	4	653
0.85	661	1.051437	1.0	4	632
0.82	643	1.080871	1.0	4	600
0.80	627	1.108453	1.0	5	575
0.78	608	1.143092	1.0	8	556
0.75	580	1.198276	1.0	12	518
0.70	484	1.435950	1.0	33	408

Overall, this pattern indicates that, with k = 15, the graph preserves local neighborhood relationships while maintaining sufficient intercluster connectivity to support community detection. Moreover, the gradual decrease in isolated nodes and the increase in the size of the largest cluster suggest that the threshold of 0.75 represents a transitional point between a sparsely connected network and an overly dense network. Consequently, its selection was grounded in structural analysis rather than arbitrary parameter specification.

The k-NN similarity graph constructed at the selected threshold (k = 15, cosine similarity ≥ 0.75) was used as input for the Leiden community detection algorithm. Clustering was performed on a similarity graph comprising 695 nodes and 147 similarity relationships with values greater than 0.75, derived from the k-NN graph. This process ultimately yielded 572 clusters and nine unclustered (isolated) indicators. These nine indicators could not be assigned to any of the clusters based on their semantic relationships and were therefore considered semantically distinct from the other indicators.

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Most communities were relatively small, indicating fine-grained semantic distinctions among the indicators. This finding suggests that the Leiden algorithm successfully avoided the artificial merging of weakly related indicators and instead generated a conservative and semantically coherent partitioning of the indicator space.

To reduce dimensionality and identify the strongest structural indicators, PaCMAP was applied to the indicators clustered using the Leiden algorithm (572 indicators). A minimum occurrence threshold of two was imposed, meaning that only indicators appearing in at least two articles were retained, whereas indicators reported in only one article were excluded from the final analysis. This filtering procedure reduced the indicator set from the original 572 indicators to 49 consolidated indicators.

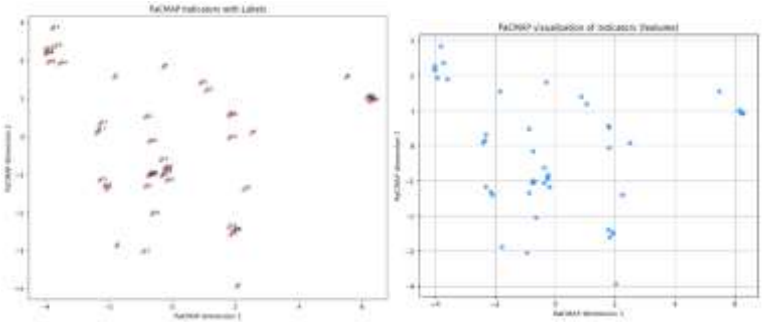


Figure 1. Two-Dimensional PaCMAP Visualization of the Filtered Indicators

The figure presents a two-dimensional map of the indicators, with each point representing one of the 49 filtered indicators, originating from the original indicator identifiers ranging from I0 to I571. Distances between points reflect the degree of similarity among indicators based on the articles in which they appeared. Points located close to one another represent indicators that commonly appeared together in similar articles and may therefore reflect closely related or overlapping concepts. Conversely, more distant points represent distinct or more specialized indicators.

The PaCMAP algorithm produces a two-dimensional representation that simultaneously preserves the local, intermediate, and global structures of the data, thereby maintaining semantic relationships among indicators. Indicators exhibiting high cosine similarity and shared neighborhood structures within the semantic embedding space appeared as dense regions in the lower-dimensional representation. These dense regions provided the basis for identifying conceptual clusters.

Two diagnostic plots, the elbow plot and the silhouette plot, were employed to identify and select an appropriate number of clusters.

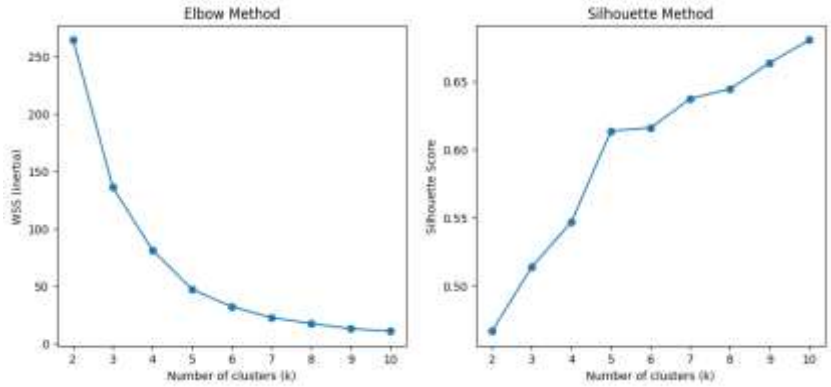


Figure 2. Determination of the Optimal Number of Clusters Using the Elbow and Silhouette Methods

In the elbow plot (left panel), the optimal number of clusters is identified by locating the point of inflection beyond which the curve begins to flatten. In the silhouette plot (right panel), the optimal number of clusters is generally associated with the highest silhouette coefficient, with larger values indicating better-defined and more clearly separated clusters.

Finally, the retained indicators were embedded in a two-dimensional PaCMAP space and grouped into seven final clusters, as illustrated in Figure 3.

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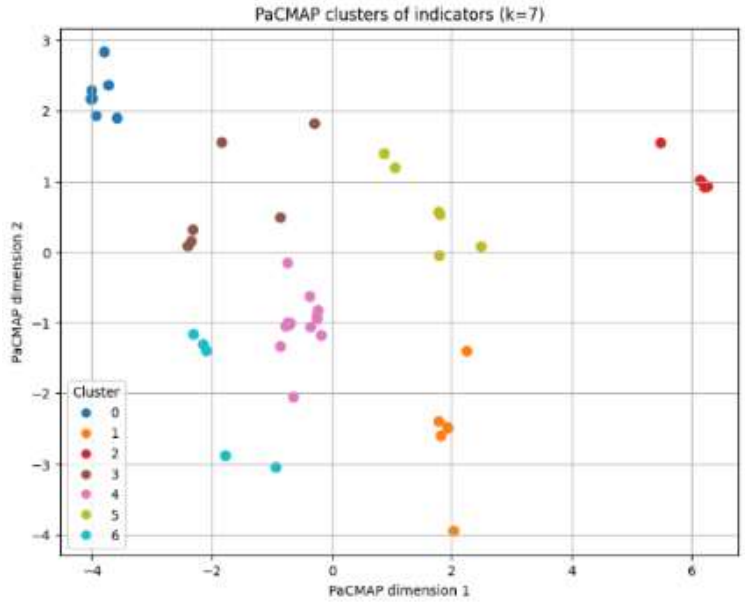


Figure 3. Final Seven-Cluster Solution for the 49 Retained Indicators in the Two-Dimensional PaCMAP Space

It should be noted that the horizontal and vertical axes do not represent specific parameters or thematic constructs. Rather, they are dimensionless projection coordinates used solely for two-dimensional visualization and to facilitate interpretation of the resulting cluster structure.

The final clustering revealed seven semantically coherent clusters, each representing a distinct thematic dimension, as presented in Table 4.

Table 4. Final Classification of the 49 Technological and Organizational Readiness Indicators Across Seven Clusters Based on PaCMAP Coordinates

Cluster Dimension	Indicator	Dimension 1	Dimension 2	Cluster ID
Strategic Leadership	Top Management Commitment and Support	-3.78983	2.830098	0
	Knowledge Sharing	-3.98862	2.165868	0
	Employee Empowerment	-3.71927	2.356929	0
	Transformational Leadership	-3.99909	2.283884	0
	Open Innovation	-4.01322	2.162501	0
	Life Cycle Thinking and Circular Production	-3.92643	1.928057	0
	Strategic Alignment of Organizational Objectives	-3.57715	1.893430	0
Industry 4.0-Based Infrastructure	Industry 4.0 Roadmap and Organizational Capability Development	2.031841	-3.948530	1
	Cloud Computing	2.252046	-1.405560	1
	Big Data Analytics	1.940723	-2.495600	1
	Predictive Maintenance	1.928834	-2.481220	1
	Decision Support Systems	1.784940	-2.398940	1
	Integration of Enterprise Resource Planning (ERP) and Manufacturing Execution Systems (MES)	1.820849	-2.602340	1
Cyber-Physical Systems (CPS) Development	Development and Standardization of Cyber-Physical Systems (CPS) Technologies	5.482867	1.542528	2
	Industry–Academia Collaboration for CPS Research and Implementation	6.265230	0.928290	2
	Standardization of Internet of Things (IoT) Communication Protocols and Networks	6.140009	1.013235	2
	Cross-Domain Data Analytics Teams for Predictive Analysis	6.149777	1.004713	2
	Data Analytics Teams for Strategic Manufacturing Optimization	6.257210	0.925259	2
	Data Preprocessing and Dimensionality Reduction Algorithms	6.211115	0.917808	2
Organizational Culture	Organizational Culture and Change Management	-1.832400	1.549290	3
	Stakeholder Collaboration and Strategic Partnerships	-2.399190	0.082016	3
	Employee Training and Learning	-0.284850	1.814957	3
	Development of Project Management Skills	-2.310710	0.312798	3
	Strategic Management and Planning	-2.338290	0.150201	3

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	Stakeholder Commitment and Responsible Collaboration	-0.855030	0.485498	3
Human Capital Development	Workforce Upskilling and Reskilling	-0.362570	-0.631090	4
	Human Resource Development and Training Programs	-0.767240	-1.050660	4
	Visionary Leadership	-0.689590	-1.012980	4
	Governmental and Policy-Based Financial Support	-0.714680	-1.037370	4
	Entrepreneurship and Innovation Development	-0.730950	-1.004360	4
	Ethical and Social Responsibility	-0.246090	-0.908840	4
	Perceived Benefits and Advantages	-0.175100	-1.182380	4
	Competitive Pressure	-0.242470	-0.950320	4
	Teamwork and Team Composition	-0.227540	-0.828240	4
	Horizontal and Vertical Integration	-0.853810	-1.338310	4
	End-to-End Technical Integration Across the Value Chain	-0.351530	-1.062340	4
	Adoption of Circular Economy Principles	-0.638390	-2.054860	4
	Integration of Lean Management and Industry 4.0	-0.734500	-0.156580	4
Lean Thinking	Optimization and Automation of Big Data Analytics Algorithms	2.491355	0.073648	5
	Managerial and Executive Leadership	1.056968	1.189295	5
	Availability of Financial Resources	1.791683	-0.055610	5
	Customer Focus	0.875950	1.389518	5
	Lean 4.0 (L4.0)	1.805635	0.525671	5
	Implementation of Lean Manufacturing Practices	1.783954	0.560311	5
Digital Workforce	Workforce Digital Skills and Competencies	-1.771360	-2.884140	6
	Development of Information Technology Infrastructure and Digital Facilities	-2.089910	-1.401060	6
	Development of and Training in Socio-Technical Design Frameworks	-0.928730	-3.046920	6
	Top Management Support	-2.140450	-1.311490	6
	Human Resource Management	-2.302080	-1.166830	6

The table presents the 49 retained indicators classified into seven conceptual clusters (Cluster IDs 0–6). Dimension 1 and Dimension 2 represent the two-dimensional coordinates generated through Pairwise Controlled Manifold Approximation and Projection (PaCMAP). These coordinates are used to visualize the relative positioning and semantic relationships of indicators and do not represent directly measurable variables. ERP = enterprise resource planning; MES = manufacturing execution system; CPS = cyber-physical systems; IoT = Internet of Things; L4.0 = Lean 4.0.

4. Discussion and Conclusion

The present study sought to identify and organize the infrastructural requirements that support the transition of small and medium-sized enterprises (SMEs) toward Industry 4.0 and Industry 5.0. Through a systematic literature review combined with computational text analysis, 695 initial indicators were extracted, semantically encoded, and progressively filtered and clustered. The application of Sentence-BERT, k-nearest neighbors (k-NN), the Leiden community detection algorithm, and PaCMAP ultimately resulted in 49 retained indicators organized into seven coherent clusters: strategic leadership, Industry 4.0-based infrastructure, development of cyber-physical systems, organizational culture, human capital development, lean thinking, and digital workforce. These findings indicate that SME readiness for advanced industrial transformation cannot be explained by technological investment alone. Instead, readiness emerges from the interaction of strategic, technological, organizational, human, operational, and institutional capabilities. This multidimensional result is consistent with previous research showing that the adoption of Industry 4.0 and Industry 5.0 in SMEs depends on an interconnected portfolio of resources and capabilities rather than on isolated digital technologies (Hansen et al., 2025; Karuppiah et al., 2023; Kee et al., 2025; Marcon et al., 2022).

The first identified cluster, strategic leadership, comprised top management commitment and support, knowledge sharing, employee empowerment, transformational leadership, open innovation, life-cycle thinking and circular production, and strategic alignment of organizational objectives. This cluster suggests that technological transition begins with strategic direction and leadership commitment. SMEs frequently operate with centralized decision structures in which owners and senior managers strongly influence investment priorities, organizational learning, resource allocation, and attitudes toward technological change. Consequently, without visible managerial support and a coherent strategic vision, digital transformation initiatives may remain fragmented or fail to progress beyond experimentation. Previous studies similarly identify management

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commitment, strategic alignment, and organizational leadership as major determinants of Industry 4.0 readiness in SMEs (Karuppiah et al., 2023; Kee et al., 2025). Hansen et al. further argue that technology alone is insufficient for digital transformation because organizational and managerial barriers can prevent firms from converting technological investments into meaningful operational improvements (Hansen et al., 2025). The inclusion of open innovation and knowledge sharing within this cluster also highlights the importance of learning beyond organizational boundaries, especially for SMEs that may not possess sufficient internal expertise to independently develop advanced digital capabilities.

The presence of life-cycle thinking and circular production within the strategic leadership cluster also demonstrates that the strategic dimension of digital transformation increasingly incorporates sustainability. The transition toward advanced industrial systems is no longer concerned solely with productivity and automation but also with resource efficiency, circularity, and longer-term environmental performance. This result aligns with research emphasizing that Industry 4.0 technologies can support sustainable production only when they are integrated with appropriate organizational and strategic practices (Jamwal et al., 2025; Kunkel et al., 2022). It is also compatible with the emerging Industry 5.0 perspective, in which organizational strategies are expected to balance competitiveness with sustainability, resilience, and human-centric value creation (Dacre et al., 2025; Martín-Gómez et al., 2024). Accordingly, strategic leadership in SMEs should be interpreted not merely as managerial sponsorship of digital investments but as the capacity to align technological transformation with broader economic, environmental, and social objectives.

The second cluster, Industry 4.0-based infrastructure, included an Industry 4.0 roadmap and organizational capability development, cloud computing, big data analytics, predictive maintenance, decision support systems, and the integration of enterprise resource planning and manufacturing execution systems. This cluster represents the technological and architectural foundations required to establish connected, data-driven production environments. The result confirms that SMEs need a basic digital backbone before more sophisticated applications can be implemented effectively. The inclusion of roadmaps and capability development is particularly important because digital transformation is generally incremental and requires firms to prioritize investments according to their existing maturity level. Previous research on SMEs has similarly emphasized the need for structured adoption models, digitalization assessment, and technology prioritization (Pandey et al., 2024; Solano García et al., 2025). The importance of cloud computing and data analytics is also consistent with the broader Industry 4.0 literature, in which scalable computation, data integration, and real-time analytical capacity are central to operational intelligence.

The identification of predictive maintenance and decision support systems within this cluster further suggests that Industry 4.0 readiness should be evaluated in terms of the capacity to transform data into operational action. Digital infrastructure becomes strategically valuable when firms can use connected data to anticipate equipment failure, support planning, improve quality, and optimize resource utilization. This interpretation is consistent with studies showing that IoT, sensing systems, and network infrastructure form the foundation of smart manufacturing applications (Abdulaziz et al., 2023; Anbalagan et al., 2024). At the same time, these technologies require interoperability and integration across organizational systems. The inclusion of ERP–MES integration therefore reflects the need to connect business-level planning with shop-floor execution. Such integration can enhance visibility and coordination but may be difficult for SMEs because of legacy systems, financial constraints, and limited technical expertise, challenges that have been widely documented in research on digital transformation barriers (Ingaldi & Ulewicz, 2025; Kumar et al., 2025).

The third cluster concerned the development of cyber-physical systems and included CPS technology development and standardization, industry–academia collaboration, standardization of IoT communication protocols and networks, cross-domain data analytics teams, strategic manufacturing optimization teams, and data preprocessing and reduction algorithms. This finding demonstrates that the transition toward advanced manufacturing requires more than the acquisition of individual digital technologies; it requires a coherent cyber-physical ecosystem capable of connecting machines, people, sensors, software, and data. Previous work on SME adoption of IoT has similarly demonstrated that technological interoperability, communication standards, infrastructure design, and technical competence are essential to the development of integrated Industry 4.0 systems (Abdulaziz et al., 2023). Practical assessments of Industry 4.0 readiness also emphasize sensors, connectivity, and industrial networks as core components of smart factory capability (Anbalagan et al., 2024).

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The inclusion of industry–academia collaboration in this cluster is particularly relevant for SMEs because advanced CPS, IoT, and analytics capabilities may exceed the internal research and development capacity of smaller firms. Collaboration with universities, technology centers, suppliers, and specialized service providers can reduce knowledge barriers and facilitate access to expertise. Similarly, the presence of cross-domain data analytics teams reflects the interdisciplinary nature of smart manufacturing. Advanced digital systems require the integration of engineering, data science, operations management, and domain knowledge rather than purely technical specialization. This result is consistent with the socio-technical perspective on Industry 4.0, according to which smart manufacturing adoption depends on the alignment of technological and organizational subsystems (Marcon et al., 2022). It is also compatible with Industry 5.0 thinking, which emphasizes collaboration between intelligent technologies and human expertise rather than technological substitution alone (Islam et al., 2025).

The fourth cluster, organizational culture, consisted of organizational culture and change management, stakeholder collaboration and strategic partnerships, employee training and learning, development of project management skills, strategic management and planning, and stakeholder commitment and responsible collaboration. These findings show that digital transformation is fundamentally an organizational change process. SMEs may possess technologies but fail to generate value from them when organizational routines, attitudes, and competencies remain unchanged. Change management is particularly important because new digital systems can disrupt established workflows, decision structures, and employee roles. Research has repeatedly shown that resistance to change and organizational inertia are significant barriers to Industry 4.0 adoption (Hansen et al., 2025; Kumar et al., 2025). Similarly, the role of stakeholder collaboration found in this cluster is consistent with studies emphasizing that sustainable digital transformation requires coordination among internal and external actors (Kunkel et al., 2022; Sampene et al., 2023).

The importance of training and project management skills further illustrates the need to translate strategic intentions into structured implementation processes. Industry 4.0 and Industry 5.0 initiatives frequently involve multiple technologies, vendors, departments, and organizational changes, making project coordination critical. Studies examining the integration of Industry 4.0 with operational excellence approaches likewise identify training, organizational culture, leadership, and structured implementation as key success factors (Joshi et al., 2024; Samanta et al., 2023). Accordingly, the organizational culture cluster reflects the absorptive and adaptive capacity of SMEs to internalize new technologies and integrate them into everyday operations.

The fifth cluster, human capital development, was the largest and included workforce upskilling and reskilling, human resource development programs, visionary leadership, policy-based financial support, entrepreneurship and innovation development, ethical and social responsibility, perceived benefits, competitive pressure, teamwork and team composition, horizontal and vertical integration, end-to-end value-chain integration, circular economy principles, and lean–Industry 4.0 integration. Although heterogeneous, these indicators converge around the broader requirement to develop organizational capabilities that enable people and structures to respond to technological change. Upskilling and reskilling are especially important because digital technologies alter both occupational tasks and competency requirements. Previous research has shown that shortages of digital skills, inadequate training, and uncertainty among employees are major barriers to Industry 4.0 implementation in SMEs (Sharma et al., 2022). Educational initiatives designed for SMEs transitioning toward Industry 5.0 similarly emphasize continuous learning and competence development (Solvang et al., 2024).

The inclusion of governmental and policy-based financial support in this cluster reflects the structural disadvantages frequently faced by SMEs. Smaller firms often lack the capital required to experiment with emerging technologies or to absorb implementation failures. Consequently, external financial support, incentives, and policy frameworks can influence readiness and reduce adoption risk. This finding corresponds with research emphasizing the financial and institutional barriers that constrain digitalization in SMEs (Ingaldi & Ulewicz, 2025; Kumar et al., 2025). The presence of perceived benefits and competitive pressure further suggests that adoption decisions are shaped by both internal expectations and external market forces. Firms are more likely to invest in digital transformation when managers perceive clear operational or strategic benefits and when competitors or supply-chain partners create pressure for technological modernization (Karuppiah et al., 2023).

This cluster also contains indicators related to circular economy, ethical responsibility, integration, and teamwork, demonstrating the increasing convergence between human capital, sustainability, and organizational integration. Industry 5.0

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explicitly frames industrial development around sustainability and human-centricity, meaning that technological readiness increasingly includes ethical and social dimensions (Dacre et al., 2025; Narkhede, Dohale, et al., 2024). At the same time, previous research has highlighted the darker side of Industry 4.0, including social disruption, technological dependence, and sustainability trade-offs (Narkhede, Chinchanikar, et al., 2024). The present findings therefore suggest that SMEs preparing for advanced industrial transformation should develop not only technical competencies but also organizational mechanisms for responsible innovation, employee involvement, and sustainable value creation.

The sixth cluster, lean thinking, comprised optimization and automation of big data analytics algorithms, managerial and executive leadership, financial resource availability, customer focus, Lean 4.0, and implementation of lean manufacturing practices. This cluster supports the proposition that digital transformation is more effective when built upon disciplined process improvement. Lean management seeks to eliminate waste, improve flow, standardize work, and create customer value, while Industry 4.0 technologies provide enhanced visibility, automation, and analytical capability. Their integration can therefore produce complementary benefits. Previous studies have demonstrated that the successful integration of Lean Six Sigma and Industry 4.0 depends on management commitment, technological readiness, employee participation, training, and data-driven decision-making (Samanta et al., 2023). Similarly, the integration of lean, green, and Industry 4.0 practices requires coordinated organizational and stakeholder drivers (Zhu et al., 2022). The identification of financial resources in this cluster also reinforces the practical reality that process modernization requires sustained investment.

The seventh cluster, digital workforce, included workforce digital skills and competencies, IT infrastructure and digital facilities, socio-technical design framework development and training, top management support, and human resource management. This cluster strongly reflects the human-centric orientation of Industry 5.0. Digital transformation requires a workforce capable of using, interpreting, and adapting to intelligent technologies, while Industry 5.0 places greater emphasis on designing technologies around human capabilities and well-being. Previous studies have identified human-centered design requirements, workforce involvement, digital competence, and employee development as critical elements of human-centered SMEs (Nazarejova et al., 2024; Zare et al., 2025). Human digital twin approaches likewise demonstrate how digital technologies can be designed to support rather than displace human participation in advanced manufacturing (Modoni & Sacco, 2023). The inclusion of human resource management and management support further indicates that workforce digitalization is not an individual employee responsibility but an organizational process requiring recruitment, training, work redesign, and supportive leadership.

Taken together, the seven clusters suggest that the transition to Industry 4.0 and Industry 5.0 in SMEs follows a socio-technical logic. Technical systems such as IoT, cloud computing, CPS, analytics, and integrated information platforms must be developed alongside leadership, organizational culture, employee capabilities, process improvement, and sustainability-oriented strategies. This interpretation is consistent with research showing that Industry 4.0 adoption is shaped by the interaction of technological and socio-organizational factors (Marcon et al., 2022). It also supports recent Industry 5.0 frameworks that position human-centricity, sustainability, and resilience as complementary to technological advancement rather than as separate objectives (Islam et al., 2025; Martín-Gómez et al., 2024). The findings therefore extend prior research by consolidating these dispersed requirements into a structured set of empirically derived thematic dimensions.

The computational methodology also contributes to the interpretation of the findings. The use of SBERT allowed indicators with similar meanings but different wording to be represented in a shared semantic space. Previous studies have demonstrated the effectiveness of sentence embeddings for detecting semantic similarity and identifying near-duplicate textual elements (Isotani et al., 2023; Rabiei Zadeh & Amirkhani, 2023). The use of graph-based clustering further supported the identification of relational structures among high-dimensional semantic representations, consistent with prior applications of contextual embeddings and graph clustering (Li et al., 2023; Mugeni & Amagasa, 2022). Likewise, the Leiden algorithm provided a systematic mechanism for identifying communities within the similarity network (Sihombing et al., 2025), whereas PaCMAP facilitated the visualization of high-dimensional relationships while preserving local and broader structural patterns (Qattous et al., 2024). Therefore, the resulting clusters were not based solely on subjective researcher judgment but were supported by a reproducible computational procedure.

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Several limitations should be considered when interpreting the findings. First, the review was restricted to English-language journal articles indexed in Scopus and Web of Science, which may have excluded relevant studies published in other languages, databases, conference proceedings, industry reports, and technical standards. Second, the final clusters were influenced by methodological choices such as the SBERT model, the value of k, the cosine similarity threshold, the minimum occurrence criterion, and the clustering and dimensionality-reduction algorithms. Alternative parameter settings or models could produce somewhat different structures. Third, the criterion requiring indicators to appear in at least two studies increased robustness but may have excluded emerging or context-specific indicators that are theoretically important but not yet widely reported. Fourth, semantic proximity does not necessarily imply causal or functional equivalence, and some indicators grouped together may operate differently across industries, countries, and levels of technological maturity. Finally, the present study synthesizes existing literature rather than directly validating the identified clusters through primary data from SMEs.

Future studies should empirically validate the seven-cluster framework using data collected directly from SMEs operating in different industrial sectors and national contexts. Survey-based research could test the reliability and construct validity of the 49 indicators and examine whether the proposed dimensions predict Industry 4.0 and Industry 5.0 readiness, adoption intensity, operational performance, resilience, and sustainability outcomes. Longitudinal research would be particularly valuable for determining how infrastructural requirements change as firms progress from initial digitalization to more advanced stages of human-centric and sustainable manufacturing. Comparative studies should also examine whether the relative importance of clusters differs across firm size, manufacturing intensity, technological maturity, and economic development level. Methodologically, future research could compare different sentence-embedding models, community-detection techniques, and dimensionality-reduction approaches to assess the stability of the cluster structure. Emerging indicators that appeared only once in the literature should also be reconsidered as the Industry 5.0 evidence base expands.

For practice, SME managers should treat the transition toward Industry 4.0 and Industry 5.0 as a coordinated capability-development program rather than a technology procurement project. Firms should begin by assessing their current position across the seven identified dimensions and identifying the most critical capability gaps. Management should establish a clear digital roadmap, ensure sustained leadership commitment, and prioritize foundational infrastructure such as connectivity, data integration, cloud services, and interoperable information systems before investing in more sophisticated technologies. Parallel investments should be made in workforce training, reskilling, change management, and socio-technical work design so that employees can effectively interact with digital systems. SMEs should also strengthen partnerships with universities, technology providers, industry associations, and public agencies to compensate for limited internal resources. Lean and continuous-improvement practices should be integrated with digitalization initiatives, while sustainability, circular economy, ethical responsibility, employee well-being, and resilience should be incorporated into technology investment decisions from the outset.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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