**Investigating the Barriers to Quality 4.0 Adoption in the Indian Manufacturing Sector: Insights and Implications for Industry and Policymaking**

**Abstract**

**Purpose:**

The research explores the shift to Quality 4.0, examining the move towards a data-focused transformation within organizational frameworks. This transition is characterized by incorporating Industry 4.0 technological innovations into existing quality management frameworks, signifying a significant evolution in quality control systems. Despite the evident advantages, the practical deployment in the Indian manufacturing sector encounters various obstacles. This research is dedicated to a thorough examination of these impediments. It is structured around a set of pivotal research questions: Firstly, it seeks to identify the key barriers that impede the adoption of Quality 4.0. Secondly, it aims to elucidate these barriers' interrelations and mutual dependencies. Thirdly, the research prioritizes these barriers in terms of their significance to the adoption process. Finally, it contemplates the ramifications of these priorities for the strategic advancement of manufacturing practices and the development of informed policies. By answering these questions, the research provides a detailed understanding of the challenges faced. It offers actionable insights for practitioners and policymakers implementing Quality 4.0 in the Indian manufacturing sector.

**Design/methodology/approach:** Employing Interpretive Structural Modelling (ISM) and Matrix Impact of Cross Multiplication Applied to Classification (MICMAC), we probe the interdependencies amongst fourteen identified barriers inhibiting Quality 4.0 adoption. These barriers were categorised according to their driving power and dependence, providing a richer understanding of the dynamic obstacles within the Technology-Organization-Environment (TOE) framework.

**Findings:** The study results highlight the lack of Quality 4.0 standards and Big Data Analytics (BDA) tools as fundamental obstacles to integrating Quality 4.0 within the Indian manufacturing sector. Additionally, the study results contravene dominant academic narratives, suggesting that the cumulative impact of organisational barriers is marginal, contrary to theoretical postulations emphasising their central significance in Quality 4.0 assimilation.

**Originality:** This research delineates specific obstacles to Quality 4.0 adoption by applying the TOE (Technology-Organization-Environment) framework, detailing how these barriers interact with and influence each other, particularly highlighting the previously overlooked environmental factors. The analysis reveals a critical interdependence between 'Lack of standards for Quality 4.0' and 'Lack of standardised Big Data Analytics (BDA) tools and solutions', providing nuanced insights into their conjoined effect on stalling progress in this field. Moreover, the study contributes to the theoretical body of knowledge by mapping out these novel impediments, offering a more comprehensive understanding of the challenges faced in adopting Quality 4.0.

**Practical implications:** This research provides concrete strategies, such as developing a collaborative platform for sharing best practices in Quality 4.0 standards, which fosters a synergistic relationship between organizations and policymakers, for instance, by creating a joint task force, comprised of industry leaders and regulatory bodies, dedicated to formulating and disseminating comprehensive guidelines for Quality 4.0 adoption. This initiative could lead to establishing industry-wide standards, benefiting from the pooled expertise of diverse stakeholders. Additionally, the study underscores the necessity for robust, standardized Big Data Analytics tools specifically designed to meet the Quality 4.0 criteria, which can be developed through public-private partnerships. These tools would facilitate the seamless integration of Quality 4.0 processes, demonstrating a direct route for overcoming the barriers of inadequate standards.

*Key Words:* Quality 4.0; Barriers; Interpretive Structural Modelling; TOE framework; Quality Management Systems; Manufacturing

**1. Introduction**

Quality 4.0 represents a pivotal shift towards data-driven organisational metamorphosis, utilising expansive datasets produced by integrated Industry 4.0 technologies for refining Quality Management Systems (QMS) (Gunasekaran *et al.*, 2019). This paradigmatic change enables organisations to support the transition from reactive to proactive quality management (Thekkoote, 2022). Quality 4.0 entails the adoption of real-time monitoring, predictive maintenance, and anomaly detection, resulting in faster identification and resolution of quality issues (Asif, 2020; Dias *et al.*, 2022), leading to an overall improvement in product quality (Dutta *et al.*, 2021). This shift towards Quality 4.0 empowers organisations to make data-informed decisions, optimise quality control processes, and improve customer satisfaction and operational efficiency (Antony *et al.*, 2023).

Establishing a digital quality management ecosystem within the framework of Quality 4.0 demands a convergence of digital processes and QMS via a central data platform (Prashar, 2023; Sureshchandar, 2022). This transformation includes integrating data-driven insights, automation, real-time monitoring and control, predictive maintenance, advanced collaboration, risk management, and compliance (Babatunde, 2020). Effective integration of Quality 4.0 demands a change in decision-making, emphasising data-driven strategies, agility, flexibility, collaboration, risk tolerance, innovation, change management, and ethical considerations (Escobar *et al.*, 2021; Maganga and Taifa, 2022; Souza *et al.*, 2022).

There are many impediments to the successful implementation of Quality 4.0, as evidenced by empirical studies (Antony *et al.*, 2022; Sony *et al.*, 2021; Zulqarnain *et al.*, 2022). Challenges include the need for robust integration of diverse digital technologies, organisational culture evolution, workforce upskilling in data analytics, IoT, AI, and concerns over data security (Asif, 2020; Dias *et al.*, 2022; Sader *et al.*, 2022). Although prior empirical investigations on Quality 4.0 offer meaningful perspectives (e.g., (Antony *et al.*, 2022; “Quality 4-0 | ASQ”, n.d.; Sony *et al.*, 2021; Zulqarnain *et al.*, 2022)), they often lack a theoretical framework to structure, categorise, and prioritise the impediments to Quality 4.0 adoption. Additionally, research focusing exclusively on barrier prioritisation frequently exhibits limited breadth, neglecting the complex interdependencies and reciprocal interactions among various deterrents potentially undermining successful Quality 4.0 assimilation. Furthermore, the existing body of literature often overlooks the broader environmental context within which new technologies are adopted. While significant attention has been paid to the technological components of such adoption processes (Maganga and Taifa, 2022; Sony *et al.*, 2020, 2021) and the internal organizational factors that facilitate or impede them (Antony *et al.*, 2023), there is a lack of detailed exploration of the external environmental factors. These include industry standards, market dynamics, regulatory policies, and socio-economic trends that critically shape technology adoption. This research gap results in an incomplete understanding of organisations' challenges, warranting an in-depth investigation encompassing all dimensions of the adoption environment to truly capture the multifaceted nature of implementing new technologies like Quality 4.0.

This research aims to fill the knowledge gaps mentioned above by examining the multifaceted obstacles to adopting Quality 4.0 in the distinct context of the Indian manufacturing sector. The Indian manufacturing sector, unlike its counterparts in highly developed nations, faces diverse challenges, including limited technological infrastructure, inconsistent digital readiness, and resource constraints (Kamble *et al.*, 2018). The Indian manufacturing sphere, a blend of traditional and cutting-edge practices, offers a broad spectrum of Quality 4.0 readiness (Chauhan *et al.*, 2021). This variability facilitates deep exploration into the impact of factors like industry type, firm size, and regional disparities on Quality 4.0 adoption. The dynamic environment, shaped by ongoing digital transformation and governmental ‘Make in India’ strategies, further allows for studying policy and infrastructure-related effects (Nimawat and Gidwani, 2021). We can better understand barriers and facilitators in transitioning economies by exploring these factors. Through comparative analyses, we can gain insights into the adaptability of Quality 4.0 frameworks across varied economic landscapes (Dutta *et al.*, 2021). Thus, this study addresses the following research questions:

*RQ1.* *What are the key barriers hindering the adoption of Quality 4.0 within the manufacturing sector?*

*RQ2. What are the relationships and mutual dependencies among the barriers hindering the adoption of Quality 4.0 within the manufacturing sector?*

*RQ3. Which barriers to Quality 4.0 adoption are most critical to address within the Indian manufacturing sector, and in what order should they be tackled to optimize the adoption process?*

*RQ4. What strategic and policy-making decisions must be informed by the hierarchy of these barriers to facilitate a more effective and efficient adoption of Quality 4.0 within the Indian manufacturing sector?*

The insights this research provides add to the existing body of knowledge in three distinct dimensions: Primarily, it propounds a theoretical categorisation of barriers to Quality 4.0 adoption grounded within the TOE framework, thereby enriching the comprehension of various obstacles. Secondly, it explicates the intricate interplay between these barriers, providing valuable insights into their dynamism throughout the adoption process. Lastly, this research yields strategic insights for industry professionals and policymakers, emphasising the overlooked environmental context’s significance in past studies(Antony *et al.*, 2022; Chiarini and Cherrafi, 2023; Maganga and Taifa, 2022).

The rest of the article is structured as follows: Section 2 examines the relevant literature on barriers to Quality 4.0 adoption. Section 3 details the approach and methodology employed to investigate the priorities of these barriers. Section 4 presents the data analysis and critical findings. Section 5 elaborates on the implications and interpretations of the results. Finally, Section 6 summarises the central insights of the study and offers recommendations for future research and practice.

**2. Theoretical Framework**

*2.1 The emerging concept of Quality 4.0*

The emergence of the Quality 4.0 paradigm has coincided with the progression of Industry 4.0, a designation posited by certain scholars and practitioners to signify the Fourth Industrial Revolution. Nevertheless, it is imperative to note that this marker currently engenders academic deliberation, lacking universal consensus at present (Asif, 2020; Babatunde, 2020; Souza *et al.*, 2022). Industry 4.0 is oriented towards the development of ‘smart factories’, underpinned by the integration of advanced digital technologies such as big data analytics, the Internet of Things (IoT), artificial intelligence, additive manufacturing, virtual reality, machine learning, and sophisticated robotics (Senna *et al.*, 2022). The principle of interconnectivity is central to Industry 4.0, enabling real-time monitoring, control, and continuous improvement of manufacturing processes (Sanchez *et al.*, 2020).

Quality 4.0 emerges as a revolutionary advancement in quality management, characterized by the use of digital technologies to innovate and enhance traditional practices. The literature presents a diverse array of dimensions that define Quality 4.0, each underscored by different authors. Gunasekaran *et al.* (2019) examine the socio-technical evolution of manufacturing in the face of digitalization, while Maganga and Taifa (2022) and Zulqarnain et al. (2022) explore the symbiotic relationship between advanced Industry 4.0 technologies and the upskilling of the workforce.

The integration and strategic use of data, as delineated by Sureshchandar (2022), and the amplification of quality performance metrics through analytics, AI, and machine learning techniques, as discussed by Antony et al. (2023), highlight the data-centric aspect of Quality 4.0. These perspectives collectively underscore the technology-driven transformation of quality systems, as noted by Xu et al. (2018) and further expounded by Zulqarnain et al. (2022), who delve into the digitalization of quality management.

The literature also suggests a requisite overhaul of organizational strategies and supply chain mechanisms to adapt to Quality 4.0, as Prashar (2023) posited. These literature findings are complemented by Chiarini and Cherrafi (2023) and Gunasekaran et al. (2019), who discuss how IoT-based data analysis can preempt disruptions, ensuring reliability and operational continuity. Babatunde (2020) states that digital intervention promotes transparency and refines supplier quality metrics.

A holistic understanding of Quality 4.0 is incomplete without considering the cultural and strategic alignment necessary for transitioning to these new technologies. This transition involves a comprehensive change management approach and investment in workforce development, as emphasized by Ranjith Kumar et al. (2022). Table 1 presents a comprehensive view of Quality 4.0 in contemporary literature.

As a theoretical lens, the TOE framework could provide a structured approach to navigating the barriers to Quality 4.0 adoption and enhancing solution effectiveness.

Table I

Summary of the dimensions of Quality 4.0 in the contemporary literature

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Author/Dimension** | **Socio-technical Evolution** | **Technology and Workforce Synergy** | **Data Integration and Analytics** | **Digital Transformation** | **Organizational Strategy Overhaul** | **Supply Chain Integration** | **Cultural and Organizational Shift** | **Workforce Development** |
| Gunasekaran et al. (2019) | Yes | No | No | No | No | No | No | No |
| Maganga and Taifa (2022) | No | Yes | No | No | No | No | No | Yes |
| Zulqarnain *et al*. (2022) | Yes | Yes | No | Yes | No | No | No | Yes |
| Sureshchandar (2022) | No | No | Yes | No | No | No | No | No |
| Antony *et al*. (2023) | No | No | Yes | No | No | No | No | No |
| Xu et al. (2018) | No | No | No | Yes | No | No | No | No |
| Prashar (2023) | No | No | No | No | Yes | No | Yes | Yes |
| Chiarini and Cherrafi (2023) | No | No | No | No | No | Yes | No | No |
| Babatunde (2020) | No | No | No | Yes | No | No | No | No |
| Ranjith Kumar *et al.* (2022) | No | Yes | No | No | No | No | Yes | Yes |
| **Consensus** | Mixed | Agreement | Agreement | Mixed | Agreement | Agreement | Mixed | Agreement |
| **Potential Organizational Outcomes** | Improved adaptability to change | Enhanced operational efficiency | Data-driven decision making | Increased process efficiency | Strategic alignment | Supply chain resilience | Cultural adaptability | Skilled labour force |

Note: "Yes" indicates the author discussed the dimension; "No" means the criteria was not a focus in their work.

*2.2. Technology-Organisation-Environment (TOE) Framework*

The TOE framework presents a comprehensive analytical approach to examining the complexities inherent in technological adoption within various industrial sectors. This framework emphasizes the tripartite interplay of technical, organizational, and environmental factors (Fattouh *et al.*, 2023). The rationale for selecting the TOE framework over other models, such as the Technology Acceptance Model (TAM) and the Diffusion of Innovations (DOI), lies in its broader and more inclusive perspective.

While TAM focuses primarily on the individual user's perceptions and attitudes towards technology, and DOI centres on the stages and rate of technology adoption within a population, the TOE framework provides a more expansive view. It incorporates the technological elements and the organizational and environmental contexts that play a significant role in the adoption process (Kouhizadeh *et al.*, 2021). This holistic perspective is particularly pertinent to the study of Quality 4.0 adoption, where external environmental factors, such as regulatory standards and market dynamics, play a critical role alongside internal technological capabilities and organizational readiness. This framework thus affords a more nuanced analysis of the multifaceted barriers to Quality 4.0 adoption, which is essential for developing comprehensive, actionable strategies for practitioners and policymakers.

The TOE framework recognizes that a complex set of factors beyond individual perceptions, including organizational readiness, structural capabilities, and the external business environment, influences the successful integration of new technologies. The TOE framework’s broad-based perspective has found applicability across a multitude of domains, including healthcare, manufacturing, agriculture, and transportation, to delve into the assimilation of avant-garde technologies, including cloud-ERP, blockchain, robotics, IoT, and AI (Gillani *et al.*, 2020; Kamble *et al.*, 2020; Orji *et al.*, 2020; Senna *et al.*, 2022). Fig 1 illustrates the dynamics of dimensions of the TOE framework in the context of Quality 4.0 adoption in manufacturing.

In the technological domain of the TOE framework, considerations revolve around infrastructure, technological advancements, and capabilities that influence an entity’s receptiveness to technology (Kouhizadeh *et al.*, 2021). This aspect elucidates potential deterrents to adoption, such as technological immaturity, workforce competency gaps, data protection concerns, and intricate system integration issues (Senna *et al.*, 2022).

In the organizational realm, the TOE framework focuses on the intrinsic characteristics of firms that shape the dynamics of technological assimilation (Orji *et al.*, 2020). Factors such as organizational size, change readiness, resource availability, managerial structure, and employee expertise are crucial in determining the successful integration of Quality 4.0 technologies in manufacturing domains (Sony *et al.*, 2021). Challenges may stem from internal resistance, financial limitations, strategic vision gaps, and inherent organizational complexities (Escobar *et al.*, 2021; Kannan and Garad, 2020). A comprehensive assessment of these dimensions is essential to identify and address resistance areas and facilitate tailored organizational change strategies. Finally, the environmental attribute of the TOE framework addresses external catalysts influencing a firm’s technological decision-making (Gillani *et al.*, 2020). These ecological attributes involve industry competition, regulatory standards, societal trends, and technological advancements (Kamble *et al.*, 2020).

Collectively, the TOE framework endows organisations with a multifaceted lens, optimising their strategic navigations in the digital metamorphosis landscape. Fig.1 depicts the TOE framework for adopting Quality 4.0 in manufacturing.

**Organization (O)**

Skilled workforce

High level of investment

Transformation at organizational and processes level

Digital strategy

Quality 4.0 benefits and ROI

**Environment (E)**

Systems/infrastructure

Regulatory framework

Standards for Quality 4.0

Interoperability and compliance

**Quality 4.0 adoption**

**Technology (T)**

BDA tools and solutions

Data security and privacy

Adaptation of Quality Management System

Knowledge management infrastructure

Integration capabilities

Fig 1. TOE Framework for Quality 4.0 Adoption in the Manufacturing Sector

*2.3 Quality 4.0 Adoption Barriers*

The emergence of Quality 4.0 heralds a transformative juncture in organisational landscapes amidst intensifying ambiguities, necessitating rigorous academic exploration to ascertain enterprises’ impediments in adopting this emergent paradigm (Chiarini and Kumar, 2022). Existing literature, albeit extensive, predominantly scrutinises specific technologies or environments, overlooking an integrated, holistic perspective. The literature primarily focuses on individual Quality 4.0 challenges, like big data (Escobar *et al.*, 2021), blockchain or IoT (Saihi *et al.*, 2023), or unique manufacturing contexts (Dutta *et al.*, 2021), thereby underscoring the necessity for a broader approach.

*2.3.1 Organisational Barriers*

Quality 4.0 adoption faces considerable organisational barriers (Babatunde, 2020). Paramount among these is the absence of strategic alignment; the transition towards Quality 4.0 often fails to secure upper management’s prioritisation, resulting in suboptimal resource allocation for requisite technological investments and skill augmentation (Antony *et al.*, 2023). Employee apprehensions, rooted in job sustainability anxieties and intricate operational metamorphoses, exacerbate these challenges (Balouei Jamkhaneh *et al.*, 2022). The lack of a distinct digital strategy and effective communication intensifies this reticence. Prevalent organisational cultures, frequently lacking agility and risk tolerance essential for successful Quality 4.0 integration, constitute another significant impediment (Dias *et al.*, 2022).

*2.3.2 Technological Barriers*

The inception of Quality 4.0 brings forth significant technological challenges that hinder its widespread uptake in the manufacturing sector (Sureshchandar, 2022). The intrinsic intricacy of these technologies mandates substantive fiscal commitments, while installation, orchestration, and sustenance phases require profound technical prowess (Maganga and Taifa, 2022). Assimilating avant-garde technologies with archaic systems becomes a monumental challenge, demanding considerable capital infusion for infrastructural overhaul (Souza *et al.*, 2022). The digital literacy gap among employees, preventing practical usage of digital tools and analysis of complex datasets, and heightened cybersecurity concerns surrounding data privacy, security, and integrity augment these complexities (Dias *et al.*, 2022).

*2.3.3 Environmental Barriers*

Externally, the adoption of Quality 4.0 is stymied by multifarious environmental deterrents. Economic instability and market uncertainty frequently deter the capital-intensive outlays intrinsic to digital metamorphosis. The regulatory maze surrounding data sanctity, privacy, and digital stewardship further complicates the adoption trajectory (Sony *et al.*, 2021). The relentless cadence of technological innovations risks rendering investments redundant, and infrastructure deficits in specific geographies could circumscribe access to pivotal technologies (Saihi *et al.*, 2023). Market rivalry, the absence of unifying standards, and fluctuating regulatory topographies present formidable challenges (Antony *et al.*, 2022).

*2.3.4 Additional Barriers*

Further impediments to Quality 4.0 adoption in the manufacturing sector, which have garnered scholarly attention, encompass the need for seamless integration of digital technologies (Ranjith Kumar *et al.*, 2022), stressing the crucial role of organisational culture and change management in transitioning to Quality 4.0 (Maganga and Taifa, 2022). Prior literature also spotlights capability voids, spotlighting the salience of human capital enhancement, robust data safeguarding mechanisms, and the primacy of performance metrics (Christou *et al.*, 2022; Sony *et al.*, 2021). Additionally, there is a focus on sector-specific adaptations, blueprints for SMEs, and the potential of Quality 4.0 to advance ecological sustainability and societal obligations (Sureshchandar, 2022). The discourse also touches upon socio-technical challenges, including labour intricacies, supply chain nuances, regulatory compliance issues, and trepidations emanating from limited Quality 4.0 comprehension (Kamble *et al.*, 2018; Singh *et al.*, 2023; Zulqarnain *et al.*, 2022).

Table II summarises barriers to quality 4.0 adoption identified by various authors.

Table II: Summary of Barriers to Quality 4.0 Adoption as Identified by Various Authors

|  |  |  |  |
| --- | --- | --- | --- |
| **Barrier Type** | **Author(s)** | **Identified Barriers** | **Implications** |
| Organisational | Babatunde (2020), Antony et al. (2023), Balouei Jamkhaneh et al. (2022), Dias et al. (2022) | Lack of strategic alignment, management prioritization, cultural rigidity, employee apprehensions | Hinders resource allocation and integration of Quality 4.0 practices |
| Technological | Sureshchandar (2022), Maganga and Taifa (2022), Souza et al. (2022), Dias et al. (2022) | Complexity of new technologies, digital literacy gap, cybersecurity concerns, legacy system integration issues | Creates technical and financial challenges in adopting Quality 4.0 |
| Environmental | Sony et al. (2021), Antony, McDermott, et al. (2022), Saihi et al. (2023) | Economic instability, market uncertainty, regulatory complexities, technological pace, infrastructural limitations | Poses external constraints and uncertainties affecting Quality 4.0 uptake |
| Additional | Ranjith Kumar et al. (2022), Maganga and Taifa (2022), Christou et al. (2022), Kamble et al. (2018), Singh et al. (2023), Zulqarnain et al. (2022) | Integration issues, organisational culture, capability gaps, sector-specific challenges, socio-technical complexities | Calls for comprehensive strategic and operational adjustments |

**3. Research method**

Fig. 2 describes the methodological approach used in the study. A comprehensive examination of the literature identified the barriers to Quality 4.0, which was subsequently validated and refined through a focus group of industry experts. The research employed an integrated ISM and MICMAC analysis approach to analyse the data. The ISM approach establishes the interrelationships among the barriers and develops the hierarchical relationship map. MICMAC analysis facilitated the identification of the root obstacles based on their driving power and dependency. This structured approach ensured a comprehensive exploration of the topic under study.

NO

Achieve the Level Partitioning of the barriers.

Develop the Structural Self-Interaction Matrix (SSIM) and convert into Final Reachability Matrix

Classification of identified barriers into the TOE Framework

Clustering of barriers into four categories to identify root causes for Quality 4.0 adoption.

Calculate the driving and dependency levels of the barriers.

YES

Is the ISM model consistent?

Develop the ISM based structural model.

Literature review

Identification of the Barriers to Quality 4.0 adoption in the Manufacturing Sector

Focus Group

Aggregate expert opinion for finalizing and establishing the contextual relationship between the barriers.

Adjusting the interpretive knowledge rule

Not satisfied

Transitivity Check

Satisfied

Interpretation of the results and analysis

Develop managerial implication.

Fig. 2. Schematic representation of the research methodology

*3.1 Identification of the Barriers to Quality 4.0 Adoption in the Manufacturing Sector*

The systematic literature review (SLR) methodology was employed in this study to identify, evaluate, and synthesise pertinent academic literature within a burgeoning and diverse field. The merits of this methodology have been well-established in extant research (Palmatier *et al.*, 2018; Snyder, 2019). The ensuing sections articulate the implemented SLR protocol steps tailored to meet the study's goals. Employing a structured, transparent protocol, the SLR aims to aggregate, critically assess, and integrate current studies, addressing a distinct research question (Tranfield *et al.*, 2003). The procedure followed includes a five-step model proposed by Denyer and Tranfield (2009), initiating a pilot search to inform literature selection criteria, conceptualize the research question, and outline subsequent phases.

Our team pursued rigorous, transparent research and developed a review protocol rooted in an articulated, answerable research question (Counsell, 1997). This question forms the cornerstone of the systematic review, directing each phase of the protocol (Nguyen *et al.*, 2018). The primary research question guiding this SLR was: "*What are the key barriers hindering the adoption of Quality 4.0 within the manufacturing sector?*"

The literature search was conducted in two methodical stages, adhering to the structured protocol. Initially, a pilot search was performed to discern the field's landscape and refine the literature selection criteria, as recommended by Denyer and Tranfield (2009). This preliminary search facilitated the identification of pertinent keywords and the establishment of inclusion and exclusion parameters. Subsequently, a focused search utilizing these keywords was executed across electronic databases to accrue relevant sources. Considering the necessity for databases that furnish extensive access to a diverse array of pertinent scholarly works spanning a defined temporal range, this study employed Elsevier’s Scopus database alongside the ISI Web of Science (WoS) – Core Collection database from Thomson Reuters. The selection of Scopus was predicated on its status as the most expansive abstract and citation database encompassing peer-reviewed academic literature (Palmaccio *et al.*, 2021). Concurrently, the WoS was chosen due to its reputation for providing comprehensive and dependable citation data for scholarly articles (Talwar *et al.*, 2021).

Rowley and Slack (2004) recommend specificity in search strings for article retrieval. We used truncated words to form four search sets, focusing on facets of Quality 4.0 in the manufacturing sector. The four distinct search strings employed in this study are delineated in Table III. The search was limited to titles, abstracts, and keywords within Scopus and WoS databases. The targeted search was initially conducted in March 2023 and complemented by a follow-up search in May 2023. Utilizing broad primary search strings that encompassed a diverse range of terminologies yielded a total of 1658 articles. These findings are systematically presented in Table 1. The numerical data depicted without parentheses signify the initial quantity of articles. In contrast, the figures enclosed within parentheses indicate the refined selection of papers chosen after a subsequent application of the inclusion/exclusion criteria established during the pilot search. Key article details were methodically recorded and organized within a Microsoft Excel database for further analysis and reference.

Table III. Database search strings and results

|  |  |  |  |
| --- | --- | --- | --- |
| **Serial No.** | **Search string/criteria** | **Scopus** | **WoS** |
| 1 | TITLE-ABS-KEY ( "Industry 4.0" AND ( "Quality Management" OR "Quality" OR  "Quality 4.0" OR "Total Quality Management" OR "Quality Control" OR ” Statistical Process Control") ) AND TITLE-ABS-KEY ( "Manufacturing" OR "Industr\*") AND ( LIMIT-TO ( SUBJAREA, "ENGI" ) OR LIMIT-TO ( SUBJAREA, "BUSI" ) OR LIMIT-TO ( SUBJAREA, "COMP" ) OR LIMIT-TO ( SUBJAREA, "DECI" ) ) AND ( LIMIT-TO ( DOCTYPE, "ar" ) ) AND ( LIMIT-TO ( SRCTYPE, "j" ) ) AND ( LIMIT-TO ( LANGUAGE, "English" ) ) | 1015  (183) | 430  (123) |
| 2 | TITLE-ABS-KEY ( "Quality Management" AND "Quality 4.0" ) AND TITLE-ABS-KEY ( "Manufacturing" OR "Industr\*") AND ( LIMIT-TO ( SRCTYPE, "j" ) ) AND ( LIMIT-TO ( SUBJAREA, "ENGI" ) OR LIMIT-TO ( SUBJAREA, "BUSI" ) OR LIMIT-TO ( SUBJAREA, "COMP" ) OR LIMIT-TO ( SUBJAREA, "DECI" ) ) AND ( LIMIT-TO ( DOCTYPE, "ar" ) ) AND ( LIMIT-TO ( LANGUAGE, "English" ) ) | 101  (15) | 56  (12) |
| 3 | TITLE-ABS-KEY ( "Data Driven Quality Management" ) AND TITLE-ABS-KEY ("Manufacturing" OR "Industr\*" ) AND ( LIMIT-TO ( SRCTYPE, "j" ) ) AND ( LIMIT-TO ( SUBJAREA, "ENGI" ) OR LIMIT-TO ( SUBJAREA, "BUSI" ) OR LIMIT-TO ( SUBJAREA, "COMP" ) OR LIMIT-TO ( SUBJAREA, "DECI" ) ) AND ( LIMIT-TO ( DOCTYPE, "ar" ) ) AND ( LIMIT-TO ( LANGUAGE, "English" ) ) | 16  (4) | (9)  2 |
| 4 | TITLE-ABS-KEY ( "Digital Quality Management" ) AND TITLE-ABS-KEY ("Manufacturing" OR "Industr\*" ) AND ( LIMIT-TO ( SRCTYPE, "j" ) ) AND ( LIMIT-TO ( SUBJAREA, "ENGI" ) OR LIMIT-TO ( SUBJAREA, "BUSI" ) OR LIMIT-TO ( SUBJAREA, "COMP" ) OR LIMIT-TO ( SUBJAREA, "DECI" ) ) AND ( LIMIT-TO ( DOCTYPE, "ar" ) ) AND ( LIMIT-TO ( LANGUAGE, "English" ) ) | 25  (0) | 6  (0) |

Inclusion criteria were English-language peer-reviewed journal articles published from 2013 to May 2023, aligning with the inception of the term ‘Industry 4.0’ (Senna et al., 2022). Exclusions were non-English articles, proceedings papers, book chapters, reviews, abstracts, theses, interviews, and non-manufacturing industry studies. This exclusion refined the search to 339 pieces across business, management, engineering, computer science, and decision sciences.

The initial screening of titles, abstracts, and keywords from 204 unique papers ensured relevance to Quality 4.0 barriers in manufacturing. Two reviewers assessed abstracts for inter-coder reliability (Miles and Huberman, 1994). Papers explicitly addressing Quality 4.0 adoption and associated barriers in manufacturing were included. An iterative review process validated the database's relevance and reliability.

The final selection of 76 articles underwent full-text review by multiple researchers. Cross-referencing and additional searches on Google Scholar, recognizing its capacity to reveal non-indexed works, expanded the final count ((Daisy) Lyu *et al.*, 2022; Kranzbühler *et al.*, 2018). The inclusion phase incorporated nine further publications identified via cross-referencing, and six additional peer-reviewed articles were found on Google Scholar, cumulating 76 articles. Fig. 3 presents the flow chart of the literature search process and the outcome of the different stages of screening the articles.

Content analysis of highly cited peer-reviewed journal articles

Keywords search

Application of the inclusion criteria (Title, Abstract and Keywords review) n = 1319 studies removed exclusive to the research field

Preliminary database Search

n = 1658

Scopus string search n = 1157(including duplicates)

WoS String search n = 501(including duplicates)

Publication included based on cross-referencing and Google Scholar search (Cross referencing n=9 and Google Scholar search = 6)

Final records retained for thematic analysis.

n = 76 (full paper review)

Application of duplicate criteria n= 135 duplicates removed

Application of duplicate criteria n= 135 duplicates removed

Total studies retained.

n = 61 (full paper review)

Total studies retained.

n = 204 (Titles, Abstract, Keywords screening)

Total studies retained.

n= 339 (Titles, Abstract, Keywords review)

Scopus=202(including duplicates)

WoS=137(including duplicates

Fig 3. Flow chart of the literature search process

Our SLR prioritized peer-reviewed articles, irrespective of journal rankings, so as not to overlook new insights from emerging journals (Loureiro *et al.*, 2020). This approach yielded a comprehensive collection of literature instrumental to understanding Quality 4.0 adoption barriers in manufacturing, contributing significantly to the existing body of knowledge.

Utilizing NVivo 12, the authors independently conducted coding, reaching a consensus on a definitive set of codes through an inductive method. NVivo's proficiency in managing extensive qualitative data, categorizing themes, and aiding in thematic analysis is well-documented (Banijamali *et al.*, 2020), and its effectiveness for systematic literature review (SLR) is acknowledged (Wohlin and Aurum, 2015; Zhang and Ali Babar, 2013).

The coding was executed in two phases. Initially, broad themes were identified, encapsulating barrier categories within the TOE framework, article typology, theoretical underpinnings, and methodological approaches. Subsequently, a more detailed coding phase discerned finer attributes within each barrier category, informed by scholarly consensus (Domenico *et al.*, 2021). The pattern analysis during reviews led to coherent thematic clusters (Templier and Pare, 2018).

The resultant coding framework included categories for barriers, theoretical frameworks used, data collection and analysis methodologies, article types, industrial contexts, geographical distribution, and suggested avenues for future research.

To ensure methodological rigour, collaborative validation with a co-researcher was employed for barrier identification (Page *et al.*, 2022). Furthermore, consultations with manufacturing quality experts via interviews and focus groups honed the list of barriers, bridging theory with industry insights (Creswell, 1999).

The literature review identified fourteen barriers to Quality 4.0 adoption in manufacturing, organized per the TOE framework and displayed in Table IV.

Table IV. Categorization of the barriers to Quality 4.0 adoption in the manufacturing sector.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| # | Barrier | Barrier Description | References | TOE Framework |
| 1 | Need for a highly skilled workforce | Quality 4.0 requires data analytics, machine learning, and artificial intelligence skills not commonly found in the traditional manufacturing workforce. Training and hiring skilled workers can also be costly and time-consuming, especially for small and medium-sized enterprises with limited resources. | Kannan and Garad (2020); Balouei Jamkhaneh *et al.* (2022); Maganga and Taifa (2022). | *Organization* |
| 2 | Need for high level of investment | Adopting Quality 4.0 requires significant investment in new technology, software, and infrastructure. High investment in Quality 4.0 may limit adoption, especially for SMEs lacking financial resources. | Daniel Küpper *et al.* (2020); Sony *et al.* (2021). | *Organization* |
| 3 | Need for agile transformation at the organizational and process level | Implementing Quality 4.0 requires dynamic reconfiguration at the organizational level and demands significant investment in new technologies, training, and potentially rehiring. This transformation can pose considerable challenges for smaller organizations with limited resources. Additionally, data security and regulatory compliance complexities, especially in highly regulated industries, hinder the adoption of Quality 4.0. | Sony *et al.*, (2021); Antony *et al.* (2022); Chiarini and Cherrafi (2023). | *Organization* |
| 4 | Outdated systems/infrastructure | Outdated systems and infrastructure can lead to incompatibility with new technologies, limited scalability, high costs of upgrades and replacements, operational disruptions, resistance to change, maintenance challenges, and security vulnerabilities. | Maganga and Taifa (2022); Ranjith Kumar *et al.* (2022). | *Environment* |
| 5 | Lack of regulatory framework | Quality 4.0 may pose significant challenges in IT security, cybersecurity, human-machine interaction, and human resource management. Lack of regulatory support leads to ambiguity in compliance requirements, inconsistent standards, potential legal issues, hindered collaboration, reduced trust, and slower technology adoption. | Raj *et al.* (2020); Sony *et al.* (2020); Dutta *et al.*, 2021; Sony *et al.* (2021). | *Environment* |
| 6 | Lack of standards for Quality 4.0 | The lack of standardized protocols leads to inefficiencies and inconsistencies due to poor levels of interoperability, data exchange, and collaboration among stakeholders, hindering benchmarking and innovation. | Asif (2020); Daniel Küpper *et al.* (2020); Laskurain-Iturbe *et al.* (2023). | *Environment* |
| 7 | Lack of standardized BDA tools and solutions | The lack of standardized BDA tools and solutions hinders Quality 4.0 adoption due to integration difficulties, inconsistent data analysis, vendor lock-in, increased costs, slower adoption, and collaboration barriers. Embracing industry-standard tools and solutions can enhance interoperability, consistency, and flexibility in Quality 4.0 initiatives. | Senna *et al.* (2022); Sureshchandar (2022). | *Technology* |
| 8 | Concerns about data security and privacy | Data security and privacy concerns hinder Quality 4.0 adoption due to increased vulnerability, regulatory compliance challenges, loss of trust, additional costs, complexity, and trade-offs between functionality and security. | Kannan and Garad (2020); Sony *et al.* (2021). | *Technology* |
| 9 | Inadequate interoperability and compliance standards | Insufficient interoperability hampers the integration of diverse technologies and systems, impeding the seamless exchange of data and information necessary for real-time quality monitoring and decision-making. The absence of robust compliance standards undermines the establishment of uniform quality practices and inhibits the widespread implementation of Quality 4.0 across industries, limiting its potential benefits. | Ali and Johl (2022); Christou *et al.* (2022); Kumar *et al.* (2022); Canbay and Akman (2023). | *Environment* |
| 10 | Need for synergistic evolution and adaptation of Quality Management System | Adaptive modifications of quality practices can hinder Quality 4.0 adoption due to resistance to change, organizational inertia, complexity of new techniques, skill gaps, limited resources, lack of top management support, and unclear ROI. | Babatunde (2020); Powell *et al.* (2022); Canbay and Akman (2023); Maganga and Taifa (2023). | *Technology* |
| 11 | Lack of digital strategy | The lack of a digital strategy hinders Quality 4.0 adoption by causing misaligned priorities, inefficient resource allocation, change management challenges, and difficulties in identifying opportunities, setting goals, adopting technology, and scaling initiatives. | Escobar *et al.* (2021); Senna *et al.*, (2022); Singh *et al.* (2023). | *Organization* |
| 12 | Uncertainty about Quality 4.0 benefits and ROI | Uncertainty about Quality 4.0 benefits and ROI makes it difficult to justify investments, causing scepticism, fostering risk aversion, impeding success measurement, leading to ineffective prioritization, misallocating resources, and slowing adoption and scaling. | Antony *et al.* (2022); 2023; Nenadál *et al.* (2022); Antony *et al.* (2023); Saihi *et al.* (2023). | *Organization* |
| 13 | Insufficient knowledge management infrastructure | Lack of knowledge of big data, unavailability of knowledge management systems and data governance create barriers to Quality 4.0 adoption by impacting decision-making, data quality, organizational structure, process efficiency, security, change management, and scalability. | Sony *et al.* (2021); Antony *et al.* (2022); Chiarini and Kumar, (2022). | *Technology* |
| 14 | Lack of integration capabilities for Quality 4.0 technology with legacy systems | The incompatibility of Quality 4.0 technology with legacy systems hinders adoption due to integration challenges, high costs, operational disruptions, resistance to change, limited functionality, data silos, and delayed ROI. Incongruity impacts employees and stakeholders, including training and changes to processes and systems. | Sony *et al.* (2020); Thekkoote, (2022); Prashar (2023). | *Technology* |

*3.2 Focus Group*

In this research, we harnessed focus group methodology to delve into the nuanced impediments of Quality 4.0 implementation in the Indian manufacturing sector. This choice is rooted in focus groups' proven efficacy in exploratory studies (Liamputtong, 2011; Hennink, 2014), providing a platform for collective insights crucial for comprehending multifaceted subjects like Quality 4.0. The focus group method's interactive essence stimulates rich dialogue, essential for unveiling the intricate interplay of barriers to Quality 4.0 adoption (Johnson and Christensen, 2017). The participants' uniform expertise and diverse experiences yield a deep yet broad exploration (Kitzinger, 1995). The focus group approach used in the study mirrors that of similar studies employing focus groups (Hsuan *et al.*, 2021; Senna *et al.*, 2022), underlining its aptness for our research aims.

This research used purposive sampling to select 17 experts from Quality 4.0 consultancy, academia, and the Indian manufacturing industry, aligning with our study's objectives on Quality 4.0 adoption. This facet of the selection process was guided by the methodological framework established by Carey & Asbury (2016) and resonates with the approaches documented in similar studies (Hsuan *et al.*, 2021; Mirzabeiki and Saghiri, 2020; Senna *et al.*, 2022; Shojaei and Burgess, 2022). This methodical selection focused on individuals possessing extensive technical knowledge in Quality 4.0 and expertise in pivotal Industry 4.0 domains, including advanced sensor-based quality control, machine learning for inspection and defect detection, digital twin technology, cloud-based management, and continuous process improvement through data analysis.

A critical element in our selection was the participants' proficiency in people and change management, each holding significant senior or supervisory roles. These selection criteria were essential, acknowledging the human factor's crucial role in effectively implementing and assimilating Quality 4.0 practices. Their ability to navigate human dynamics in technological and procedural changes was a key consideration. This approach guaranteed a group with homogenous Quality 4.0 expertise, fostering profound discussions and detailed examination of specific barriers. Simultaneously, we ensured diversity in their manufacturing industry backgrounds, which is vital for a broad perspective. This heterogeneity was crucial in understanding the widespread challenges to adopting Quality 4.0 in the Indian manufacturing context. Table V presents a complete profile of the seventeen focus group participants.

Table V.

Expert profiles of the participants in the focus groups

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Expert No.** | **Technological Expertise** | **Manufacturing Sector** | **Designation** | **Total Years of Work Experience** | **Change Management/People Management/Supervisory Level Experience** |
| #1 | Industrial Engineering, Smart Manufacturing and Industrial Robotics, AI, and IoT in Quality Management Quality Control, QMS, Robotics | Automotive manufacturing | Vice President -Quality and Innovation | 20 | 12 |
| #2 | Data Analytics, Process Automation, Data Visualization and Business Intelligence, Machine Learning, Process Automation, Quality Control | Medical Device Manufacturing | Chief Quality Officer | 9 | 5 |
| #3 | Smart Manufacturing and Industrial Robotics, Quality Control, Industry 4.0, Edge Computing and Fog Computing | Robotics manufacturing | Global Head -QMS, Robotics | 10 | 6 |
| #4 | AI and IoT in Quality Management, Smart Manufacturing | Semiconductor Manufacturing | Senior Vice President  Manufacturing and Quality Management. | 12 | 7 |
| #5 | Machine Learning, Lean Manufacturing, AI Simulation, Data Science and Predictive Modeling Quality Control. | Industrial machine tools manufacturing | Head- Manufacturing and Quality | 11 | 7 |
| #6 | Big data and analytics, system integration, cybersecurity, Lean Manufacturing, Quality Assurance | Audio-Video Equipment Manufacturing | General Manager- Quality | 9 | 5 |
| #7 | Operational Excellence, Digital Transformation, Lean Manufacturing, Quality Assurance | Metal manufacturing | Head - Quality and Operational Excellence | 11 | 8 |
| #8 | Industrial IoT, Quality Management Systems, Quality Assurance, Big Data Analytics | Clothing and textiles manufacturing | Director - QSE ( Quality, Safety, Environment ) | 8 | 5 |
| #9 | Data Science and Predictive Analytics, Blockchain and Distributed Ledger Technology, Smart Manufacturing, and Industrial Robotics | Telecommunications Equipment Manufacturing | Associated Vice President- Quality Assurance and Product Integrity | 11 | 7 |
| #10 | Cloud Computing and SaaS Solutions, Sensor Technology and Industrial Internet of Things (IIoT), Digital Transformation, Quality Management | Agriculture Equipment Manufacturing | Vice President -Quality and R&D | 13 | 9 |
| #11 | Sensor Technology and Industrial Internet of Things (IIoT), Quality Management Systems and Compliance | Footwear manufacturing | Associate Director of Quality and Compliance | 17 | 12 |
| #12 | Intelligent Sensors and Condition Monitoring, Digital Twin and Simulation Modelling, Quality Management Systems and Compliance | Consumer Goods Manufacturing | Regional Director - Quality System & Compliance | 10 | 8 |
| #13 | Robotics and Automation, Artificial Intelligence and Machine Learning, Data Science and Predictive Analytics, Quality Control, Process Automation | Automotive Components Manufacturing | Regional Director - Quality System & Compliance | 16 | 12 |
| #14 | Cybersecurity and Network Security, Big Data Analytics and Data Science, Internet of Things (IoT) and Data Analytics, Quality Control, Process Automation | Electronics Assembly Manufacturing | Head- Service Excellence & Information Security | 14 | 10 |
| #15 | Cloud Computing and DevOps, Advanced Analytics and Optimization, Industrial Internet of Things (IIoT) and Industrial Automation, and Quality Management. | Computer Manufacturing | Vice President -Quality Engineering and DevOps | 12 | 8 |
| #16 | Quality 4.0, Big Data Analytics, Internet of Things (IoT), Cyber-Physical Systems, Artificial Intelligence in Quality Management | Consulting | Senior Consultant- IoT Solutions Business | 15 | 12 |
| #17 | Quality 4.0, Blockchain Technology, Cloud Computing, Digital Twins, Data Security in Quality Management | Consulting | Principal Consultant- Cloud/AI/ML/IoT/Blockchain | 20 | 16 |

This diverse group was divided into two focus groups of 9 and 8 participants. The existing literature on optimal focus group dynamics informed the decision to use two focus groups and the specific group sizes (Guest *et al.*, 2017). Smaller group sizes, typically between 6 and 10 participants, are recommended to ensure in-depth discussion and individual contribution while avoiding dominance by any single participant (Hennink, 2014). Additionally, conducting two focus groups allowed for comparing and validating findings across groups, enhancing the reliability of the results (Liamputtong, 2011).

In our study on Quality 4.0 adoption in the Indian manufacturing industry, a comprehensive focus group methodology was employed, structured to yield insightful and aligned discussions with our research aims. Initially, participants were informed about the study's objectives and methods in the pre-session preparation phase, including the basics of Interpretive Structural Modeling (ISM) and MICMAC analysis. This stage was crucial for ensuring participants understood the goals and analytical techniques, allowing them to engage effectively in the discussions.

The study comprised two focus group sessions moderated by a research team member to mitigate bias. The first session included nine experts, and the second, eight. Each focus group session lasted approximately one hour, adhering to the temporal guidelines established in existing literature (Mirzabeiki and Saghiri, 2020; Senna *et al.*, 2022). Each session started with ice-breaking activities to create a conducive environment, as recommended in the literature (Krueger and Casey, 2014). Utilizing Liamputtong’s (2011) single-purpose focus group moderation technique, the discussions were explicitly steered to examine the dyadic relationships between identified barriers.

Participants also engaged in an ISM exercise, following the approach of Kamble et al. (2018), to systematically visualize and assess the interconnections among Quality 4.0 barriers. This interactive element was pivotal for garnering multi-dimensional insights (Hennink, 2014). The moderation technique ensured that all participants contributed, maintaining the focus on the study’s objectives.

Post-session data were analyzed using the ISM technique and MICMAC analysis. The findings were then validated by the panel of experts, reinforcing the credibility and reliability of the conclusions. Finally, these focus group insights were integrated with other research components, such as the theoretical framework and literature review. This integration provided a comprehensive understanding of the barriers to adopting Quality 4.0, enhancing the overall depth and rigour of the study. Participants' expertise in change management and leadership roles enriched our understanding of the human and organizational dimensions of Quality 4.0, augmenting existing sector knowledge.

*3.3. ISM-MICMAC Analysis*

This research employs an integrated ISM-MICMAC method to elucidate barriers to adopting Quality 4.0 within the Indian manufacturing sector. ISM is a robust method for discerning and analysing the interconnections among elements within complex systems, transforming theoretical models into structured visual depictions that reveal variable hierarchies and relationships (Kamble *et al.*, 2020). Unlike techniques such as the Analytic Hierarchy Process (AHP), which presupposes independence among variables, and the Decision-Making Trial and Evaluation Laboratory (DEMATEL), suited for smaller data sets, the ISM methodology excels at capturing and representing dynamic complexities inherent in the problem domain, hence its application in examining Quality 4.0 interlinked barriers (Balci and Surucu-Balci, 2021).

ISM is a systematic methodology composed of clearly delineated stages. The current research drew guidance from the works of (Kamble *et al.*, 2020; Senna *et al.*, 2022) to implement the ISM approach. The initial phase involves the identification of pivotal variables. Subsequently, interconnections representing distinctive influence patterns within the Structural Self-Interaction Matrix (SSIM) are documented. The SSIM-based analytical model delineates the dynamic interplay between factors pertinent to adopting Quality 4.0. Each variable or parameter within this model can influence or be influenced by others, establishing a network of relationships crucial for practitioners to understand. These interrelationships among variables can take one of the following types:

* V: Parameter i acts as a catalyst for parameter j, suggesting that enhancements in i will likely drive improvements in j.
* A: Conversely, parameter j is the catalyst for parameter i, indicating that changes in j will directly affect i.
* X: Parameters i and j are interdependent; each one mutually reinforces the other, creating a feedback loop that can amplify effects in both directions.
* O: Parameters i and j operate independently; neither has a discernible impact on the other's performance.

The research employed a logical binarisation process to distil the intricate interdependencies identified within the Structural Self-Interaction Matrix (SSIM) into an interpretable schema. This conversion elucidates the directional influences among the parameters by transforming the SSIM into an Initial Reachability Matrix (IRM). Each relational typology within the SSIM was substituted with a binary equivalent, simplifying the matrix and enhancing its utility for practitioners. This binary codification allows for a straightforward tracing of influence pathways between parameters, facilitating a clearer understanding of their relational dynamics within the context of Quality 4.0 adoption. The following steps outline the transformations made to facilitate this transition from the SSIM to the IRM:

* When the relationship type is 'V' (i influences j), the (i,j) element in the IRM is assigned a value of 1 (indicating influence). Conversely, the (j, i) is set to 0 (showing no effect from j to i).
* For the 'A' type relationship (j influences i), the (i,j) element is assigned a 0, while the (j, i) element is set to 1.
* In the case of an 'X' type bidirectional relationship, both the (i,j) and (j, i) elements are assigned a 1, reflecting the mutual influence.
* Where the relationship is 'O', indicating no influence, both the (i,j) and (j, i) elements are assigned a 0.

The ensuing stage embarks on an analytical scrutiny of the Initial Reachability Matrix (IRM), inspecting for transitivity by probing direct routes between variables via a third intermediate variable. If such a path exists, it is marked as transitive, assigning a ‘1\*’ to the corresponding IRM element. When a connection exists between variable’ i’ and ‘j,’ and ‘j’ is connected to ‘k,’ it implies an indirect relationship between ‘i’ and ‘k.’ Consequently, the matrix’s element (i, k) is modified from ‘0’ to ‘1\*’ to represent this indirect association. The culmination of this process is the Final Reachability Matrix (FRM), encapsulating transitive relationships among variables. Subsequently, the FRM transforms, resulting in a conical matrix instrumental for level partitioning. Each variable’s reachability, antecedent, and intersection sets are defined during this phase. The reachability set consists of the variable and others it influences or directs toward an objective.

Conversely, the antecedent set comprises the variable and other parameters impacting it or facilitating its attainment. A variable is assigned a level when its intersection set matches its reachability set. The iterative repetition of this procedure gives all variables to specific groups. Ultimately, the variables acting as connectors within each class are incorporated into an ISM-based model to capture their relationships. This approach provides a clear and visually intuitive representation of the interconnections among the variables.

MICMAC analysis explicates driving-dependence relationships among variables, pinpointing impactful or susceptible elements within the system(Digalwar *et al.*, 2022). MICMAC analysis thus assists in identifying dominant drivers, external influencers, reciprocally linked factors, and system connectors, which ultimately aids in comprehending system complexity, guiding decision-making, and developing effective strategies to address identified factors (Kamble *et al.*, 2018). This insight aids strategic interventions to enhance system outcomes (Balci and Surucu-Balci, 2021).

MICMAC analysis discerns the influence and dependency of elements within a system through a FRM. Each variable's driving power is quantified by summing its row in the FRM, while its dependency power is ascertained by adding its corresponding column entries. This data is then depicted in a driving-dependence diagram, stratifying variables into four clusters. The *Autonomous Cluster* contains variables with minimal driving and dependency, indicating limited interaction within the system. The *Dependent Cluster* comprises variables with high dependency but low driving power, reflecting their influenced state by other variables. In the *Linkage Cluster*, variables exhibit high driving and dependence, suggesting they are influential yet also influenced within the system. The *Independent Cluster*, crucial for strategic focus, includes variables with substantial driving power and minimal dependency, marking them as pivotal in influencing system dynamics without being significantly affected by other variables. These independent variables are integral in the strategic implementation of Quality 4.0, serving as focal points for initiating change.

**4. Analysis and Results**

Through an extensive literature review and validation via a focus group, the researchers identified fourteen obstacles that impede the adoption of Quality 4.0. The study established the interrelations between the barriers, yielding ninety-one distinct interaction pairs. These interactions were discerned and delineated via focus group dialogues, subsequently manifested in the SSIM, as depicted in Table III. The present research transformed the SSIM matrix into the IRM and afterwards checked it for transitivity. The study utilized a Python-based algorithmic approach for conducting the transitivity check, a pivotal step in confirming the consistency of the inferred relationships among the variables within the SSIM. The transitivity check's core objective is to validate if variable A is related to variable B and if variable B is connected to C. A must also be associated with C for the system's relations to be considered transitive and logically coherent.

The algorithmic procedure involves several steps executed through Python scripting: Firstly, the SSIM is encoded into a matrix form where binary values represent the relationships. Next, matrix elements are systematically compared to identify and affirm transitive links. Any identified inconsistencies are flagged for review, ensuring that the resultant matrix satisfies the transitive property across all variable interactions. This algorithmic method, underpinned by Python’s computational efficiency, provides a robust and systematic validation of the SSIM, thereby reducing the susceptibility to human error (Onososen *et al.*, 2022). The utilization of such an algorithmic approach in systems analysis is well-documented in the literature for its accuracy and reproducibility (Saka *et al.*, 2020).

The partitioning of the FRM matrix, representing the fourteen obstacles, was accomplished through progressive iterative processes, with the outcomes of this stratification process presented in Table VIII. In the formation of Table VIII, the variables were arranged in a hierarchical structure based on their reachability and influence within the matrix. The FRM was instrumental in this process as a foundation for determining the level of partitioning. For each variable, three distinct sets were delineated:

* The 'reachability set' encompasses the variable itself and all other variables it may influence, illustrating the scope of its impact towards achieving an objective.
* The 'antecedent set' includes the variable and any other variables influencing it, representing the factors contributing to its activation or fulfilment.
* The 'intersection set' identifies the common elements between the reachability and antecedent sets.

A variable is then positioned at a particular level within the hierarchy when its reachability set and intersection set coincide, signifying that it does not influence any other variable of a higher level. Through the iterative application of this method, all variables are categorized into discrete groups, reflecting the stratified nature of their influence and reachability.

The Final Reachability Matrix (FRM) analysis elucidates a stratified influence hierarchy among the barriers to Quality 4.0 adoption. Level I is characterized by obstacles that are most susceptible to influence by other variables within the system, encompassing barriers 1, 2, and 3. Due to their high dependency, these barriers indicate outcomes rather than drivers of change within the Quality 4.0 adoption landscape.

Conversely, Level V identifies barrier 6 as the paramount influencer, exerting significant driving power across the system. Barriers in Level II are 10, 12, 13, and 14, and those in Level III are 4, 5, 8, 9, and 11. The sole occupant of Level IV, barrier 7, wields influence downwards but is also subject to the impact of higher-level barriers, marking it as a secondary driver in the system. A detailed inspection of barriers in Levels V, IV, and III underscores the prominence of environmental factors, with barriers 6, 4, 5, and 9 belonging to the ecological dimension. These findings accentuate the environmental barriers as critical within the Indian manufacturing context, necessitating a meticulous delineation and explication of each. The articulated significance of these barriers sheds light on their pervasive impact on the Quality 4.0 implementation process, offering actionable insights into the specific environmental contingencies in the Indian context. Such insights are invaluable for practitioners and policymakers strategizing for Quality 4.0 integration, providing a clear indication of environmental considerations that may dictate the pace and trajectory of adoption.

*-----------------------------------------------------------Insert Table VI here--------------------------------------------------*

Table VI.

Structured Self-Interaction Matrix (SSIM) depicting barriers to Quality 4.0 adoption.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Barrier (i/j)** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **11** | **12** | **13** | **14** |
| **1** | - | O | O | O | O | O | O | O | O | A | O | A | O | A |
| **2** |  | - | O | A | O | O | A | O | O | A | O | O | A | A |
| **3** |  |  | - | O | O | O | O | O | O | A | O | A | A | A |
| **4** |  |  |  | - | O | O | O | O | O | V | O | V | O | V |
| **5** |  |  |  |  | - | A | A | X | V | V | O | O | V | V |
| **6** |  |  |  |  |  | - | V | V | V | V | V | O | O | V |
| **7** |  |  |  |  |  |  | - | V | V | V | O | O | O | V |
| **8** |  |  |  |  |  |  |  | - | X | O | V | O | V | V |
| **9** |  |  |  |  |  |  |  |  | - | V | O | O | V | O |
| **10** |  |  |  |  |  |  |  |  |  | - | O | A | O | X |
| **11** |  |  |  |  |  |  |  |  |  |  | - | O | V | V |
| **12** |  |  |  |  |  |  |  |  |  |  |  | - | O | X |
| **13** |  |  |  |  |  |  |  |  |  |  |  |  | - | O |
| **14** |  |  |  |  |  |  |  |  |  |  |  |  |  | - |

Table VII.

Final reachability matrix (FRM) illustrating barriers to Quality 4.0 adoption.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Barrier (i/j)** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **11** | **12** | **13** | **14** | **Driving Power** |
| **1** | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| **2** | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| **3** | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| **4** | 1\* | 1 | 1\* | 1 | 1\* | 0 | 0 | 1\* | 1\* | 1 | 1\* | 1 | 1\* | 1 | 12 |
| **5** | 1\* | 1\* | 1\* | 1\* | 1 | 0 | 0 | 1 | 1 | 1 | 1\* | 1\* | 1\* | 1 | 12 |
| **6** | 1\* | 1\* | 1\* | 1\* | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1\* | 1\* | 1 | 14 |
| **7** | 1\* | 1 | 1\* | 1\* | 1 | 0 | 1 | 1 | 1 | 1 | 1\* | 1\* | 1\* | 1 | 13 |
| **8** | 1\* | 1\* | 1\* | 1\* | 1 | 0 | 0 | 1 | 1 | 1\* | 1 | 1\* | 1 | 1 | 12 |
| **9** | 1\* | 1\* | 1\* | 1\* | 1\* | 0 | 0 | 1 | 1 | 1 | 1\* | 1\* | 1 | 1\* | 12 |
| **10** | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1\* | 11\* | 1 | 7 |
| **11** | 1\* | 1\* | 1\* | 1\* | 1\* | 0 | 0 | 1\* | 1\* | 1\* | 1 | 1\* | 1 | 1 | 12 |
| **12** | 1 | 1\* | 1 | 1\* | 0 | 0 | 0 | 1\* | 0 | 1 | 1\* | 1 | 1\* | 1 | 10 |
| **13** | 1\* | 1 | 1 | 0 | 1\* | 0 | 0 | 1\* | 1\* | 0 | 1\* | 1\* | 1 | 1 | 10 |
| **14** | 1 | 1 | 1 | 1\* | 1\* | 0 | 0 | 1\* | 1\* | 1 | 1\* | 1 | 1\* | 1 | 12 |
| **Dependence Power** | **12** | **12** | **12** | **9** | **9** | **1** | **2** | **10** | **9** | **10** | **10** | **11** | **11** | **11** |  |

Table VIII.

Level partitioning outcomes of the FRM matrix

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Barrier** | **Reachability Set** | **Antecedent Set** | **Intersection Set** | **Level** |
| **1** | 1 | 1,4,5,6,7,8,9,10,11,12,13,14 | 1 | I |
| **2** | 2 | 2,4,5,6,7,8,9,10,11,12,13,14 | 2 | I |
| **3** | 3 | 3,4,5,6,7,8,9,10,11,12,13,14 | 3 | I |
| **4** | 4,5,8,9,10,11,12,13,14 | 4,5,6,7,8,9,11,12,14 | 4,5,8,9,11,12,14 | III |
| **5** | 4,5,8,9,10,11,12,13,14 | 4,5,6,7,8,9,11,13,14 | 4,5,8,9,11,13,14 | III |
| **6** | 4,5,6,7,8,9,10,11,12,13,14 | 6 | 6 | V |
| **7** | 4,5,7,8,9,10,11,12,13,14 | 6,7 | 7 | IV |
| **8** | 4,5,8,9,10,11,12,13,14 | 4,5,6,7,8,9,11,12,13,14 | 4,5,8,9,11,12,13,14 | III |
| **9** | 4,5,8,9,10,11,12,13,14 | 4,5,6,7,8,9,11,13,14 | 4,5,8,9,11,13,14 | III |
| **10** | 10,12,13,14 | 4,5,6,7,8,9,10,11,12,14 | 10,12,13,14 | II |
| **11** | 4,5,8,9,10,11,12,13,14 | 4,5,6,7,8,9,11,12,13,14 | 4,5,8,9,11,12,13,14 | III |
| **12** | 4,8,10,11,12,13,14 | 4,5,6,7,8,9,10,11,12,13,14 | 4,5,10,11,12,13,14 | II |
| **13** | 5,8,9,11,12,13,14 | 4,5,6,7,8,9,10,11,12,13,14 | 5,8,9,11,12,13,14 | II |
| **14** | 4,5,8,9,10,11,12,13,14 | 4,5,6,7,8,9,10,11,12,13,14 | 4,5,8,9,10,11,12,13,14 | II |

*4.1. Development of the ISM-based structural model*

A directed graph (digraph)—is a visual depiction comprising nodes connected by directional arrows that articulate the relational hierarchy and influence pathways among variables, as determined by level partitioning. In constructing the digraph, the study utilizes the IRM as a foundational guide to map the directional influences among barriers to Quality 4.0 adoption. The process commences with creating a conical matrix in a lower triangular configuration, aligning obstacles according to their hierarchical status derived from the level partitioning process (as depicted in Table VIII). This structured approach underpins the visual representation on the digraph, where barriers are positioned from the uppermost echelon, denoting significant influence to the lower echelons, indicative of lesser effect.

The preliminary digraph is then developed by connecting barriers with directed edges representing the interactions ascertained by the reachability matrix. These connections denote a direct relationship, with an arrow from barrier i to j evidencing this link. Subsequent refinement of the digraph entails the removal of transitive relations to isolate and highlight the primary connections. The resulting digraph is then annotated with descriptors to evolve into the ISM model, as shown in Fig. 4. This ISM is marked by a clear hierarchical order, absent of recursive or feedback loops, offering an intelligible visual narrative of the influence patterns, thereby enhancing the understanding of the systemic interdependencies affecting Quality 4.0 adoption.

Lack of standards for Quality 4.0 (6)

Outdated systems/infrastructure (4)

Lack of standardized BDA tools and solutions (7)

Inadequate interoperability and compliance standards (9)

Concerns about data security and privacy (8)

Lack of integration capabilities for Quality 4.0 technology with legacy systems (14)

Need for synergistic evolution and adaptation of Quality Management System (10)

Need for highly skilled workforce (1)

Need for agile transformation at organizational and process level (3)

Need for high level of investment (2)

Uncertainty about Quality 4.0 benefits and ROI (12)

Insufficient knowledge management infrastructure (13)

Lack of regulatory framework (5)

Lack of digital strategy (11)

Organisation (O)

Technology (T)

Environment (E)

**Fig. 4** ISM-based model showcasing barriers to Quality 4.0 adoption and categorised under the TOE framework.

*4.2. Quality 4.0 adoption barriers based on MICMAC analysis.*

The study utilised the FRM as a fundamental resource and calculated the driving and dependence powers to support the MICMAC analysis. The methodology described above resulted in Fig. 5, which visually presents four distinctive groups based on driving power and dependency. Notably, none of the barriers are categorised within the autonomous group, denoting that all barriers significantly influence one another without being isolated or independent from the overall system. The second group encompasses dependent barriers 1, 2, 3, and 10. Barriers categorised under this group demonstrate a low driving power but a substantial dependence power, highlighting their reliance on most other barriers to implement Quality 4.0 effectively. Moreover, these barriers have a limited ability to influence other obstacles.

The third group comprises linkage barriers, including barriers 4, 5, 8, 9, 11, 12, 13 and 14. These barriers exhibit strong driving power and dependence power. Their defining characteristic is their highly dynamic nature, which significantly impacts other barriers and is correspondingly influenced by them. This interconnectedness makes it challenging to assess the beneficial changes to the overall system. The fourth category includes independent barriers, notably barriers 6 and 7. These manifest robust driving power and minimal dependence power, enabling them to significantly impact most other barriers in the system while remaining largely unaffected by them. Consequently, the study identifies these barriers as fundamental to successfully adopting Quality 4.0.

A picture containing text, screenshot, number, line

Description automatically generated

12,13

14

8,11

4,5,9

Autonomous Barriers

Independent Barriers

Linkage Barriers

Dependent Barriers

Fig. 5. MICMAC Analysis illustrating barriers to Quality 4.0 adoption.

**5. Discussion**

*5.1. Interconnectivity among barriers to Quality 4.0 adoption*

This research employs the TOE framework and ISM to analyse pivotal barriers influencing the adoption of Quality 4.0, highlighting their interconnectedness and industry impact. Our research findings underscore two significant obstacles to adopting Quality 4.0 in the Indian manufacturing industry: *the lack of standards for Quality 4.0* (barrier 6) and *the lack of standardised BDA tools and solutions* (barrier 7). These barriers demonstrate significant driving power but low dependence. The salience of these barriers within the Indian context may result from the predominant Western-centric approach of current research, which frequently neglects the distinct geographic and local challenges faced across diverse regions(Kamble *et al.*, 2018; Senna *et al.*, 2022). Hence, it is plausible that developed nations, with advanced technological infrastructures and robust regulatory frameworks, might have addressed standardisation challenges, diminishing their relevance as hindrances(Raj *et al.*, 2020). Interestingly, our findings complement previous research calling for progressive standards in Quality 4.0 for the manufacturing industry(Asif, 2020; Canbay and Akman, 2023; Zulqarnain *et al.*, 2022).

Our study identifies two primary barriers impeding the adoption of Quality 4.0 in Indian manufacturing: *the lack of standards for Quality 4.0* (barrier 6) and *the lack of standardised BDA tools and solutions* (barrier 7), showing significant driving influence but minimal dependence. The salience of these barriers within the Indian context reflects a Western-centric bias in current research, often overlooking region-specific challenges (Kamble et al., 2018; Senna et al., 2022). With their superior technology and regulations, developed countries may have mitigated such standardization issues (Raj et al., 2020). Our results align with calls for enhanced Quality 4.0 standards in manufacturing (Asif, 2020; Canbay and Akman, 2023; Zulqarnain et al., 2022), underscoring the need for regionally tailored approaches.

Our study reveals that *inadequate interoperability and compliance standards* (barrier 9) play a significant yet moderately influential role in Quality 4.0 adoption within the Indian manufacturing industry, contrasting with lesser impact observed in Western contexts (Antony, McDermott, et al., 2022; Sony et al., 2021). The fragmented nature of Indian manufacturing, dominated by independent SMEs, results in limited standardization (Kamble et al., 2018; Raj et al., 2020). The manufacturing ecosystems in Western countries are more unified, as noted by Horváth and Szabó (2019), which contrasts with other systems. This disparity emphasizes the contextual variation in barrier impact, further highlighted by the *need for high level of investment* (barrier 2) and *uncertainty about quality 4.0 benefits and ROI* (barrier 12) (Antony et al., 2023; Balouei Jamkhaneh et al. 2022), demonstrating the complex adoption dynamics of Quality 4.0 in this region.

In India's manufacturing sector, marked by fragmentation and SME dominance, Quality 4.0 adoption faces challenges like inconsistent technology uptake and limited resources for digital transformation, contrasting with advanced Western counterparts. This fragmentation necessitates a tailored Quality 4.0 approach, mindful of India's unique industrial dynamics and digital maturity. Echoing this, Maganga and Taifa (2022) identify similar hurdles in Tanzania, while Horváth and Szabó (2019) note opportunities for smaller firms in Industry 4.0. Raj et al. (2020) further stress the need for strategies suited to developing economies' infrastructural and financial realities, highlighting the importance of region-specific approaches in adopting Quality 4.0.

This study analyses barriers to adopting Quality 4.0 in India's manufacturing sector, encompassing technological, organizational, and environmental factors. It uncovers that environmental obstacles, particularly the *lack of standards for Quality 4.0* (barrier 6) and *inadequate interoperability and compliance standards* (barrier 9), significantly influence firms' uncertainty, compounded by *outdated systems and infrastructure* (barrier 4) and *the lack of a regulatory framework* (barrier 5), leading to irregular adoption and application. This finding underscores the critical, yet often overlooked, role of the environmental obstacles in Quality 4.0 adoption, exhibiting substantial influence with limited dependence. This insight necessitates urgent calls for policy interventions in developing countries, especially those in nascent socio-economic phases, encompassing standardization of Quality 4.0 practices, establishment of regulatory frameworks, and enhancement of digital infrastructure (Kamble et al., 2018; Babatunde, 2020; Sureshchandar, 2022). Contrasting with prevailing literature that focuses on technological and organizational issues, our findings highlight environmental challenges specific to India's manufacturing sector (Antony, McDermott, et al., 2022; Sony et al., 2021), underscoring the need for region-centric research (Horváth and Szabó, 2019).Top of Form

In India's manufacturing sector, critical technological barriers to Quality 4.0 adoption include *lack of standardized BDA tools and solutions* (barrier 7), demonstrating high driving power. Other obstacles, including *concerns about data security and privacy* (barrier 8), *insufficient knowledge management infrastructure* (barrier 13), *need for synergistic evolution and adaptation of Quality Management System* (barrier 10), *lack of integration capabilities for Quality 4.0 technology with legacy systems* (barrier 14), present moderate driving and dependence power (Sureshchandar, 2022), collectively depicting a fragmented technological landscape that hampers Quality 4.0 implementation.

Top of Form

Contrary to prevailing academic views, our research suggests that organizational barriers such as the *need for high level of investment (*barrier 2*)*, *need for agile transformation at organizational and process level* (barrier 3) and *need for highly skilled workforce* (barrier 1), except for the notable “Lack of Digital Strategy” (barrier 11), play a limited role in driving Quality 4.0 adoption, a finding that initially seems counterintuitive given the widely accepted significance of organizational factors in Quality 4.0 adoption (Antony et al., 2023; Antony, McDermott et al., 2022; Babatunde, 2020; Sony et al., 2021). This observation can be attributed to factors like the initial neglect of digitalization in India's manufacturing sector due to inadequate government initiatives, which has slowed comprehensive digital strategy development (Raj et al., 2020). Additionally, the sector's fragmentation and the dominance of resource-constrained SMEs have hindered the adoption of advanced technologies compared to developed nations (Dutta et al., 2021). These findings highlight the critical need for region-specific studies to fully grasp the obstacles to Quality 4.0 adoption within the Indian framework (Horváth and Szabó, 2019). This methodology is crucial for uncovering insights and challenges specific to India, diverging from the dominant perspectives often found in Western-centric literature.

The ISM-based hierarchical model, graphically details the interaction of TOE framework elements with barriers in India's manufacturing sector. It illustrates how these factors collectively influence the adoption of Quality 4.0, emphasizing their interconnected nature. For instance, the lack of standardized BDA tools in SMEs is compounded by insufficient regulatory frameworks, resulting in fragmented Quality 4.0 adoption and interoperability issues. This interconnected nature of barriers indicates that Quality 4.0 transcends mere technological advancement, signalling a shift in quality management approaches. Addressing these challenges necessitates strategic initiatives encompassing all aspects of the TOE framework, including public-private partnerships, educational programs, supportive policymaking, and organizational agility, to implement Quality 4.0 effectively.

This study utilises MICMAC analysis to substantiate the central role of barriers within the Quality 4.0 framework, elucidating their complex interrelations (Stentoft et al., 2021). Current literature reveals a disparity in focusing on organizational over environmental barriers in Quality 4.0 adoption within manufacturing (Antony, McDermott, et al., 2022; Sony et al., 2020, 2021b), with ongoing debate about environmental variables' specific impacts (Sureshchandar, 2022). Quantifying these impacts remains challenging, leaving gaps in understanding (Sony et al., 2022). Consequently, more research is needed to comprehensively assess the roles of environmental factors in adopting Quality 4.0 (Asif, 2020).

*5.2 Policymaking, Industry, Research, and Theoretical Implications*

This study identifies critical internal and external barriers to Quality 4.0 in Indian manufacturing, highlighting the need for collaborative solutions involving stakeholders and policymakers for effective integration.

*5.2.1 Implications for Policy Development*

This research emphasizes the strategic imperative for policymakers to engage with international standard-setting bodies, industry consortia, and technology partners for Quality 4.0 policy development. Key initiatives should include active participation in global consortia to shape Quality 4.0 standards, adopting international standards such as ISO 9001 for quality management (Chiarini and Kumar, 2022), ISO/IEC 27001 for information security management (Culot et al., 2021), and IEC 62264 for enterprise-control system. Such initiatives are fundamental to adequate Quality 4.0 integration, addressing critical barriers like 5, 6, 9, and 14.

Robust data governance frameworks must use BDA tools and platforms effectively, manage data privacy and security concerns, and ensure compliance with government regulations (Amat-Lefort *et al.*, 2023). These data governance frameworks can be developed referencing various international standards addressing extensive data management, processing, and governance, such as ISO/IEC 27000 family of standards (Culot *et al.*, 2021), NIST Big Data Interoperability Framework, IEEE Big Data Standards(“Ieee big data governance and metadata management (2957) | ieee big data governance and metadata management(2957)”, n.d.), W3C Semantic Web Standards(“Semantic web - w3c”, n.d.), and data privacy and security standards such as General Data Protection Regulation (GDPR) in the European Union(“General Data Protection Regulation (GDPR) – Official Legal Text”, n.d.).

This study highlights the need for policy support in developing robust communication infrastructures essential for Quality 4.0, advocating for high-speed data networks, possibly via 5G or fibre-optics (Maganga and Taifa, 2023), and policies promoting IoT and edge computing integration with standardized communication protocols in manufacturing systems.

Quality 4.0 represents a significant shift in quality management, necessitating integrated digital strategies, especially for SMEs. Indian manufacturing faces challenges such as limited technology integration and resource constraints for SMEs (Kamble et al., 2018). Policies must support the development of digital capability, fostering digital culture, skill advancement, data governance, and cybersecurity. This approach is vital in developing nations, where disparities between SMEs and large corporations in digital strategies for Quality 4.0 are pronounced (Horváth and Szabó, 2019; Senna et al., 2022). Policymaking should focus on bridging the digital divide and enabling inclusive Industry 4.0 technology adoption (Thekkoote, 2022).

*5.2.2 Implications for Industry*

This study accentuates the adoption of international standards to fill the gap in Quality 4.0-specific benchmarks for practitioners in India's industry. Organizations are encouraged to collaborate with global consortia, standardization committees, and technology partners. Adhering to standards such as ISO 9001, ISO/IEC 27001, and IEC 62264 is pivotal, laying a robust foundation for Quality 4.0 adoption and addressing challenges like data security and interoperability (Culot et al., 2021), thereby ensuring a streamlined transition to advanced quality management practices.

This study proposes a structured, phased approach for integrating standardized BDA tools into Quality 4.0 (Escobar et al., 2021). Initially, it involves identifying significant organisational data needs and selecting suitable analytics mechanisms (Escobar et al., 2021). Subsequently, evaluating existing BDA tools for integrability, scalability, and cybersecurity is critical (Kamble et al., 2018). Vendor support and user community engagement are essential for tool reliability (Sanchez et al., 2020). Open-source BDA tools offer customizable, cost-effective alternatives (Amat-Lefort et al., 2023). The next step is to develop a standardization strategy and a comprehensive roadmap, adhering to data governance standards (Culot et al., 2021). The final phase entails tool implementation and employee training, addressing barriers to Quality 4.0 adoption in manufacturing. This approach can help mitigate barriers 3, 7, 8, 9, and 14, contributing to successful Quality 4.0 adoption in the manufacturing industry.

This study highlights the importance of seamless communication infrastructure in Quality 4.0 adoption for industry practitioners, emphasizing robust integration of data from advanced digital technologies (Dutta et al., 2021; Balouei Jamkhaneh et al., 2022). Enterprises should adopt cloud solutions and real-time data processing to merge new technologies with existing systems, enhancing interoperability (Senna et al., 2022; Bajic et al., 2023). Effective communication requires standard protocols and interfaces for IoT devices and edge computing integration (Christou et al., 2022). The infrastructure supporting cloud applications, big data analytics, and real-time processing is vital (Zulqarnain et al., 2022). Additionally, Quality 4.0 necessitates interdepartmental collaboration and workforce development to operationalize these digital tools effectively (Balouei Jamkhaneh et al., 2022; Maganga and Taifa, 2022). A robust communication infrastructure is critical to navigating barriers 2, 3, 4, 5, 8, 10, and 14 in adopting Quality 4.0 within Indian manufacturing.

The study emphasizes the need for comprehensive digital strategies encompassing clear goals, digital culture, technology investment, data governance, and cybersecurity (Thekkoote, 2022). The starting point is to assess current digital capabilities, including a cost-benefit analysis of technology acquisition (Escobar et al., 2021). Workforce upskilling and system modifications are vital for successful Quality 4.0 integration (Sureshchandar, 2022). Implementing data management solutions and establishing KPIs to track progress and effectiveness is crucial (Christou et al., 2022; Dutta et al., 2021; Zulqarnain et al., 2022). By adopting a comprehensive digital strategy, Indian manufacturing organisations can navigate the challenges of Quality 4.0 adoption and overcome barriers 1,3, 7,8 and 11-13(Ranjith Kumar *et al.*, 2022).

*5.2.3 Implications for Research*

Based on the findings of this study, there are significant implications for future research in Quality 4.0. This research underscores the need for a comprehensive investigation into the diverse environmental factors influencing the adoption of Quality 4.0, aiming to bridge gaps in academic understanding. These economic, political, social, and technological dimensions are critically examined for their specific impacts on adoption processes. The study stresses the role of regional dynamics in shaping Quality 4.0 strategies, particularly in fragmented, SME-dominated sectors like India's, addressing issues like limited standardization and digital readiness variance. It advocates for regionally tailored solutions, considering investment capabilities, technology access, and regulatory compliance.

Region-specific analysis is crucial to grasp the challenges and opportunities of adopting Quality 4.0 across different geographical contexts. This localized approach aids in developing strategies aligned with regional needs, enhancing Quality 4.0 implementation efficacy. For example, research in India may focus on integrating Quality 4.0 in SME-centric sectors, while European studies might address automated, regulated environments. Such methodologies are vital for crafting region-appropriate solutions, ensuring sustainable Quality 4.0 initiatives, and driving continuous innovation in quality management.

Furthermore, the study contributes to scholarly discourse by emphasizing the importance of international standards in Quality 4.0, suggesting industry-specific adaptations, and identifying research barriers. It advances the understanding of Big Data Analytics (BDA) tool standardization in Quality 4.0 (Sanchez et al., 2020; Escobar et al., 2021; Amat-Lefort et al., 2023), proposing a structured approach to address standardization gaps. The research also presents a conceptual framework for integrating advanced digital technologies in manufacturing, discussing infrastructural needs (Dutta et al., 2021; Kamble et al., 2018; Senna et al., 2022; Amat-Lefort et al., 2023), and outlines a systematic strategy for digital transformation, setting a foundation for future strategy evaluations in Quality 4.0 adoption (Babatunde, 2020; Escobar et al., 2021; Thekkoote, 2022; Sureshchandar, 2022), thereby connecting theoretical and practical aspects in this evolving domain.

*5.2.4 Theoretical Implications*

This study enriches the Quality 4.0 theory by integrating environmental and regional factors, enhancing its scope and practicality. It introduces an expanded framework considering technological, organisational, and ecological elements, recognizing their profound impact on Quality 4.0 adoption across different regions. This broader view fosters a more comprehensive approach to quality management in the digital age. Additionally, the research reassesses organizational barriers in Quality 4.0, especially their reduced impact in contexts like India, guiding more effective integration strategies.

Theoretically, the study highlights the essential role of international standards in Quality 4.0 implementation, aiding in overcoming technological and organizational challenges in manufacturing (Chiarini & Kumar, 2022). It advocates for a standardized Big Data Analytics (BDA) model, adhering to global data management norms, thus deepening the understanding of Quality 4.0 complexities (Escobar et al., 2021; Amat-Lefort et al., 2023). The proposed infrastructural framework focuses on swift data transmission and IoT integration, contributing to theoretical insights on infrastructural necessities for Quality 4.0 (Dutta et al., 2021; Christou et al., 2022; Zulqarnain et al., 2022). The study also outlines a strategic digital transformation plan in quality management, emphasizing Key Performance Indicators (KPIs) for practical Quality 4.0 application in manufacturing (Dutta et al., 2021; Zulqarnain et al., 2022).

**6. Conclusions**

The evolving domain of Quality 4.0 remains under-researched, especially regarding the barriers to its integration in the manufacturing sector. Existing studies on this topic often lack a robust theoretical underpinning, compromising their generalizability and applicability. The absence of standardised Quality 4.0 norms and Big Data Analytics tools were identified as primary barriers. Therefore, managers and policymakers must address these to ensure successful Quality 4.0 integration. Interestingly, the findings underscore the significance of the environmental obstacles, as they have high driving power yet low dependency, especially compared to most technological and organisational challenges. This emphasis was anticipated because many Quality 4.0 environmental factors remain emergent. The Indian manufacturing context, characterised by its fragmented structure, limited Quality 4.0 awareness, insufficient infrastructural readiness for Industry 4.0, and several other challenges, further substantiates the dominance of environmental barriers. These results have significant implications for the evaluation and decision-making process to assess the effect of the ecological dimension on adopting Quality 4.0 technologies and practices. Further, the findings suggest that organisations should build comprehensive evaluation mechanisms that account for the exigencies resulting from their effect. Technological hurdles should be prioritised following the environmental dimension, while organisational barriers should receive the least priority in the evaluation process.

The current study was limited to identifying barriers to Quality 4.0 adoption within the manufacturing industry. A natural progression of this work is to identify and analyse the obstacles relevant to the service sector. Further, the methodology used in the study resulted in developing the dependence relationships between the identified barriers. Future studies should target identifying casual relationships. Additionally, as the present study examined the interrelationships between the identified obstacles and the driving power and dependency in the context of the Indian manufacturing sector, work needs to be done in other country settings to establish whether the identified barriers and their interrelationships hold in those diversified contexts.

Additionally, future research should attempt to structurally model the causal relationships, which could complement the dependent relationships identified through this study. As Quality 4.0 is a developing domain and due to the uncertainty of the evolving Industry 4.0 technologies, future modelling work will have to be conducted periodically to understand the changing nature of the dependencies and to understand barriers better. Finally, further research must examine the dependency links identified through this study more closely using structural equation modelling, an essential step in confirming the relationships.

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