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Article

The Role of Quantum Machine Learning in the Transition from Industry 4.0 to Industry 5.0

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Abstract: The current review's goal is to examine the strategic significance of Quantum Machine Learning (QML) as a technology tool or strategic enabler of Industry 5.0, the approaching industrial revolution. To summarize and categorize the most common forms, antecedents, and outcomes of sustainable innovation, the primary objective of this study is to systematically identify and critically evaluate the literature on sustainable innovation in Industry 5.0 since January 2020. A thorough search and review of 5984 scholarly articles were identified during the systematic review, and 36 publications were chosen by a cyclic filtration for a careful review in the fields of Industry 5.0 and QML to analyze the articles' contents. The findings demonstrate that QML provides a revolutionary improvement in decision-making platforms, system security, and data analytics in Industry 4.0. By taking into consideration a methodical and critical assessment of the research manuscripts, the proposed survey offers readers an impactful insight into the functions of quantum machine learning as an enabler to Industry 5.0 processes. QML is emphasized as a key driver for secure, intelligent, and sustainable industrial ecosystems through QML-assisted designs across various verticals, such as smart healthcare, manufacturing, digital twins, and Cobots, as this review methodically examines the enabling technologies shaping the Industry 5.0 vision. It also highlights how QML can improve decision-making, ensure post-quantum security, optimize resources, and speed up the realization of human-centric, energy-efficient, and resilient Industry 5.0 systems as quantum computing advances.
Keywords: Quantum Machine Learning, Industry 4.0, Industry 5.0, cyber-physical systems (CPS), Systematic Review.

1. Introduction

Quantum machine learning (QML) is an emerging multidisciplinary subject that combines machine learning and quantum computing to address and more precisely resolve complex computational challenges. With its focus on human-centricity, sophisticated automation, and intelligent, collaborative technology, the next phase in the development of industrial systems is known as Industry 5.0, which aims to provide more individualized, flexible, and human-inclusive industrial settings in contrast to Industry 4.0, which was largely concerned with automation, connection, data-driven efficiency, unemployment, etc. [1-3]. By combining human creativity and intuition with the power of sophisticated AI, robots, and autonomous systems, this paradigm shift allows enterprises to customize products to meet the demands of each unique customer while also optimizing production [4]. The potential of Industry 5.0 to address issues with workforce integration(employment), sustainability, and adaptive manufacturing, where human-robot collaboration is essential, makes it relevant. The QML, an emerging multidisciplinary subject, uses machine learning and quantum computing to tackle challenging computational issues like ultra-high-speed data processing with high precision, data security, etc. [5-8], and enhances the efficiency of traditional machine learning algorithms by utilizing quantum mechanical ideas such as superposition, entanglement, and quantum parallelism. In the challenging areas, especially those requiring large-scale data processing and optimization tasks, quantum computing holds the possibility of exponential speedups [9-11] and of becoming the most computationally demanding tasks in artificial intelligence (AI), as it may be able to overcome computational constraints that plague traditional machine learning systems by leveraging quantum techniques. The QML enables speed and scalability of industrial systems, which could cause a paradigm shift to Industry 5.0 [12]. Real-time decision-making, intelligent optimization, and processing power are becoming essential as the smart industries move toward more complex and adaptable manufacturing processes. Despite their strength, traditional machine learning methods are becoming computationally incapable of managing the massive volumes of data and complex models present in Industry 5.0 applications [13-15] where a potential remedy is provided by quantum-enhanced machine learning, which makes it possible for quicker processing, more effective data analysis, and better-quality optimization methods. Because of its ability to improve automation, overcome the constraints of existing AI models, and facilitate complicated decision-making processes in human-centric industrial systems, QML is indispensable to Industry 5.0. Some QML-based critical transitions of Industry 4.0 to Industry 5.0 [16-18] are shown in Figure 1.

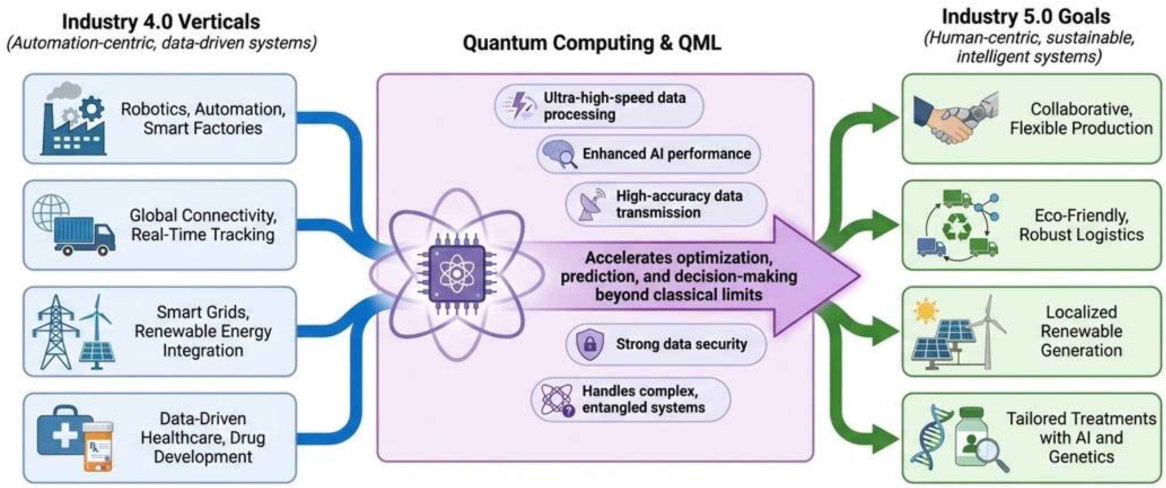

Figure 1. Some QML-based critical transitions of Industry 4.0 to Industry 5.0 (16–18)

The review and study of QML is crucial to implementing how new technologies become more Industry 5.0-aligned for better social practices to help communities [19-20]. The analysis of future QML research that is compulsory to assist researchers in achieving these breakthroughs and converge to Industry 5.0 served as the foundation for our systematic review. On the advice of [5,6,21], who confirmed that dedicated QML studies are desperately needed given their significance for Industry 5.0's implementation and success, and in this regard, our focused contributory study and investigation aligned with this mankind transition. The current review examines the strategic importance of QML as a technological instrument or a strategic facilitator of the upcoming industrial revolution. Furthermore, demonstrates the crucial intuitions that QML has included in a promising field of study [22-23]. Our analysis, therefore, seeks to identify the types and results of QML as a strategic enabler. Prior extensive studies on technical tools and techniques for Industry 5.0 and beyond did not clearly address QML and failed to identify its types, antecedents, and outcomes [24]. In a broad spectrum, previous systematic reviews have also been carried out [25]. Since Industry 5.0 is still a term with sluggish industrial sector acceptance, the current article would add to the knowledge base, urging Industry 5.0 to embrace QML by highlighting its antecedents, uses, and results. To comprehend the players that propel sustainable innovation, the present assessment is also crucial for Industry 5.0, particularly for the small and medium-sized businesses that dominate the sector [26]. Research in this field is essential to understanding these cutting-edge technologies [27] and, more recently, claimed that understanding the innovation phenomena in Industry 5.0 and other related fields is crucial [28].

The main goal of the present review is to comprehensively identify and critically assess the literature on sustainable innovation in Industry 5.0 from January 2020 to compile and classify the most prevalent forms, antecedents, and results of sustainable innovation. This in-depth review provides substantial Industry 5.0 real-world implications via QML. To perform an in-depth critical overview of literature (from 2020), this work seeks to improve the understanding of QML in Industry 5.0 and to categorize its types, antecedents, and outcomes in facilitating sustainable innovation. The following research domains are the main interests of the present work:

- to investigate how Industry 5.0's human-centric, dependable, and sustainable automation is made possible by QML, with a focus on enhanced decision-making, explainability, and mass customisation.

- to use QML to overcome the limitations of traditional computing in high-speed, data-intensive Industry 5.0 contexts for anomaly detection, predictive maintenance, and real-time optimization.
- to use QML to integrate federated learning, edge-cloud topologies, and real-time anomaly detection for low-latency, scalable, and privacy-preserving intelligence in Cyber-Physical Systems (CPS) and the Industrial Internet of Things (IIoT).
- to improve explainability and system resilience in Industry 5.0 by using QML to create quantum-aware decision support systems that facilitate real-time, multi-objective optimization, predictive analytics, and human-in-the-loop cooperation.

This review presents the first-of-its-kind, multi-faceted critical discourse on the revolutionary intersection of Quantum Machine Learning (QML) and Industry 5.0, focusing not only on the technical promise but also on the human-oriented, ethical, and socio-industrial consequences of such a convergence. In contrast to previous disjointed or technology-oriented reviews, it presents an integrated framework that positions QML as a strategic enabler for Industry 5.0 with objectives including resilience, personalization, sustainability, and intelligent human-machine collaboration, via quantum-amplified data analytics, optimization, and decision-making. It identifies key knowledge gaps by mapping QML capabilities against critical Industry 5.0 pillars through enhanced application-specific analysis. Presents a new vision of "Quantum-Aware Human-in-the-Loop Systems," emphasizing QML's potential to enhance, not displace, human intelligence through explainable, ethically sound AI. It also introduces a novel stratification of technical and strategic worth, ranging from the surpassing of classical bottlenecks to the construction of national competitiveness, innovation ecosystems, and post-quantum governance models. This work provides an integrative roadmap spanning application spaces, ethical aspects (Quantum Explainable AI), and infrastructural strategies (federated learning, edge-cloud quantum deployment), thereby providing grounds for interdisciplinary QML participation in Industry 5.0.

2. Methodology

The systematic reviews employ four steps to ensure data collection adheres to a strict, open, and repeatable procedure: database and keyword identification; Relevant articles are screened and selected, their eligibility is determined, and the selected articles are included in (Figure 2) [29,30]. The UGC Care II, a comprehensive database of research articles with detailed bibliographic information, was used to find publications for this study. UGC Care II is frequently used for bibliometric analysis in several domains, such as Industry 5.0 and QML [31], and it provides a database of 6270 entries, including 2530 indexed papers and 3740 references [32]. In QML and Industry 5.0, there is a substantial (54%) overlap between the WoS and Scopus databases [15,33]. To avoid this conflict, the well-known and established database for doing thorough and significant assessments in Industry 5.0 and QML is the UGC Care II. Our study followed the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to provide an open and reproducible review process [34-36]. The present methodology of review analysis, the PRISMA flow diagram, is shown in Figure 2.

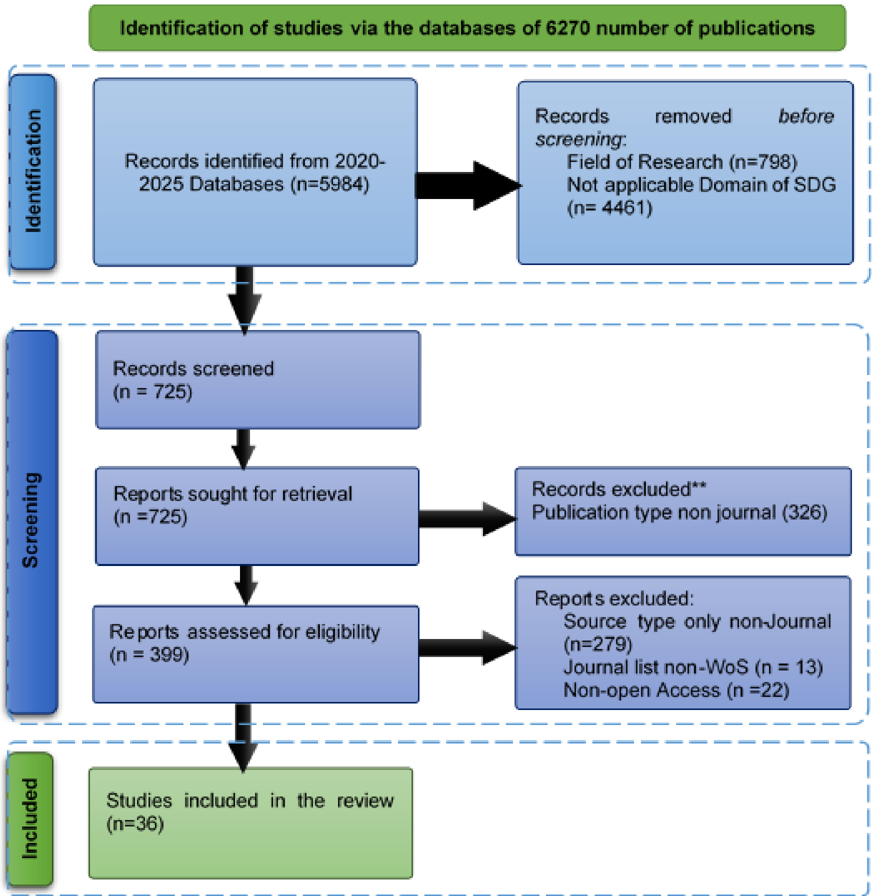

Figure 2. The methodology of the PRISMA 2020 flow diagram of the present review and analysis

To locate the most relevant articles faster, the authors first employed a list of keywords in the topics [37-38]. The idea of QML and Industry 5.0, as well as the opinions and validation of two subjective experts, were taken into consideration while selecting the search terms. QML, Industry 5.0, Quantum Computing, Artificial Intelligence, CPS, Human-Centric Manufacturing, Intelligent Automation, Human-AI Collaboration, Smart Factory, and Edge Quantum Computing are some of these terms [39]. The researchers also utilized a list of keywords that included QML and Industry 5.0 to choose studies that were carried out between 2020 and the present day. The writers employed the aforementioned string in January 2020 to search for pertinent literature using keywords, abstracts, and titles [40–42]. The titles and abstracts of the papers were then examined by the researchers. The requirements for inclusion were as follows:

(1) The article is available through the authors' university email.

(2) the language used is English; and

(3) The focus is on sustainable innovation in QML and Industry 5.0. The 2020–2025 term (until July 3, 2025) is then provided. 36 papers published between 2020 and the end of July 2025 were appropriate for the latter in the analysis that followed. Lastly, thorough literature studies in the fields of Industry 5.0 and QML were used to analyze the articles' substance [43-44]. Each work underwent a thorough debate and examination on an individual basis to resolve disagreements and come to a consensus [45]. The following steps were used to carry out the systematic review: 5984 documents in all were found during the identification step by conducting thorough searches across many scholarly databases. Before screening, 4461 items were eliminated for being outside the relevant Sustainable Development Goals (SDG) domain, and 798 entries were eliminated for being irrelevant to the designated Field of Research. 725 records underwent screening based on titles and abstracts following the first elimination procedure. 326 items were eliminated during this stage based on the kind of publication, mostly because they weren't journal papers. A total of 399 reports were requested for full-text retrieval and evaluation as part of the Eligibility Assessment. After careful review, 279 papers were eliminated because they were not journal sources, 13 reports were eliminated because

they were not listed in the UGC Care II database, and 22 reports were eliminated because they were behind paywalls or were not open access. 36 papers ultimately satisfied the eligibility requirements and were added to the systematic review during the inclusion stage. To understand collaboration patterns among researchers and institutions involved in QML and Industry 5.0 studies. Tool Used: VOS viewer, data Source: extracted metadata from UGC Care II journals, with inclusion Criteria: authors who have at least one publication or more than 3 co-authorship links shown in Figure 3. This figure also shows that each node represents an author's name, and connecting terminals between the nodes represent coauthors of their research community.

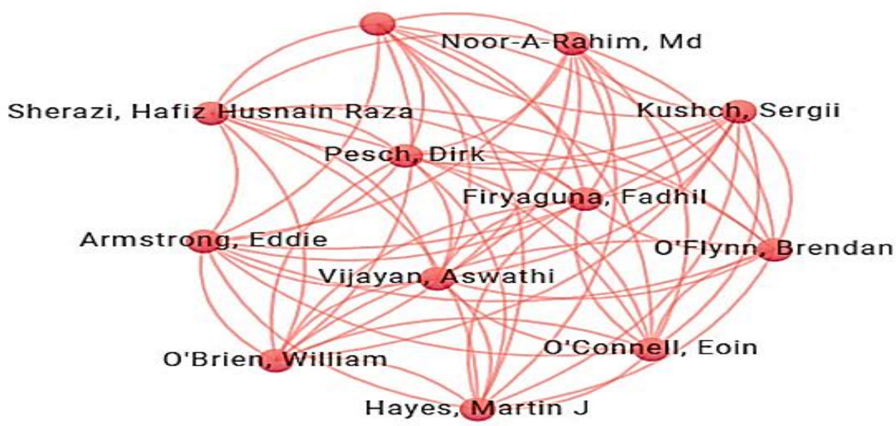

Figure 3. Co-authorship analysis

These papers meet the inclusion criteria, which include open-access availability, relevance to the SDGs, and peer-reviewed journal status, and they also align with the study's focus. Year-wise publication and citation trends are two essential bibliometric indicators that help in assessing the evolution, impact, and research maturity of a scientific domain. The significance, particularly in a review on topics like Quantum Machine Learning (QML) and Industry 5.0, is shown in Figures 4 and 5.

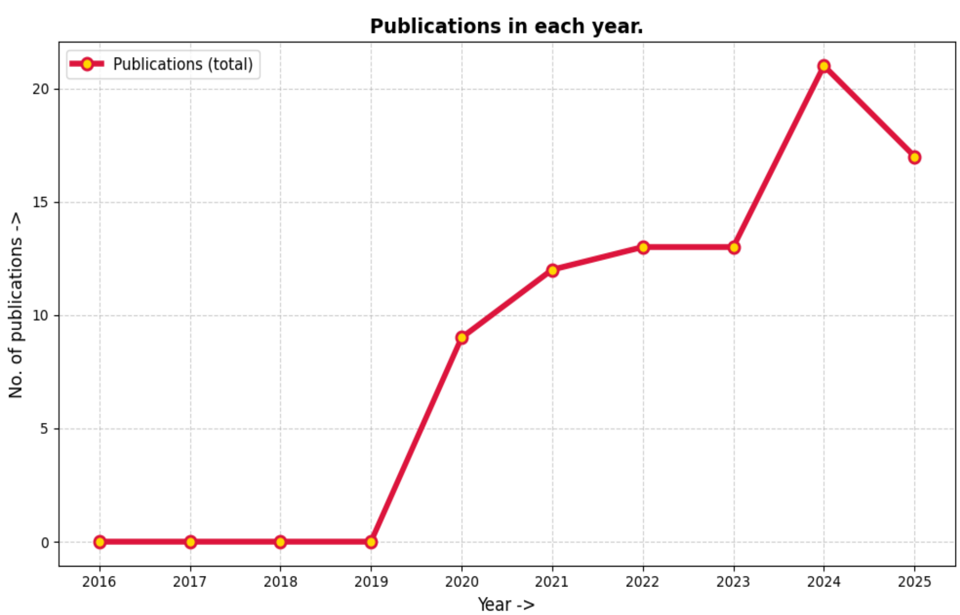

Figure 4. Year-wise publication analysis

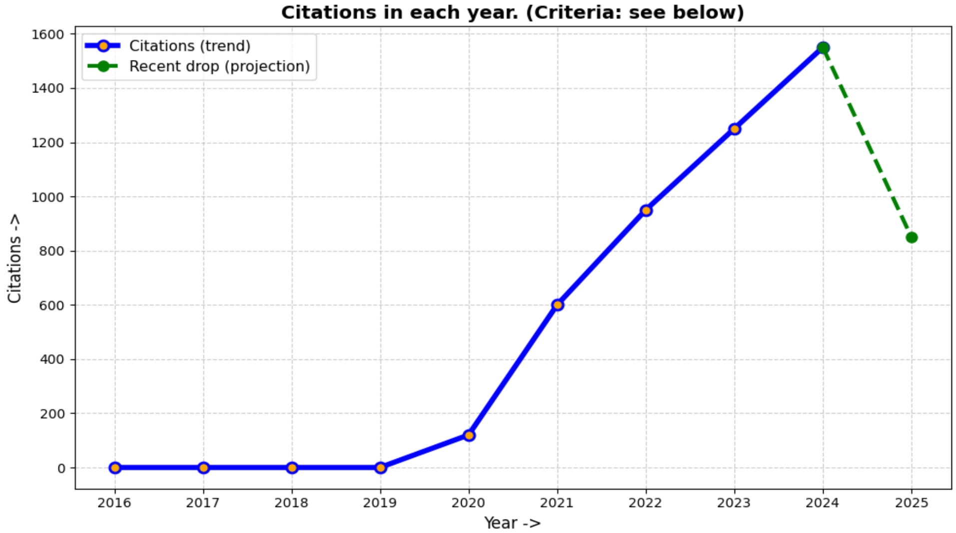

Figure 5. Year-wise citation of the article

Figure 4 describes the research attention on QML. From 2016 to 2019, there were hardly any research papers or publications coming out, but after 2019, the number of publications related to QML just popped up because researchers were recognizing the potential and depth of application of QML. Figure 5 describes the impacts of QML on other researchers and how much they are referencing and building upon the work done in this field. Just like publication 2016-2018, the number of times researchers cited the article in this domain is negligible, but from 2019 onwards, hints of a ripple appear.

3. Data Review and Analysis

The sources (journals) of the selected 36 manuscripts that were chosen for the analysis are presented in Figure 6.

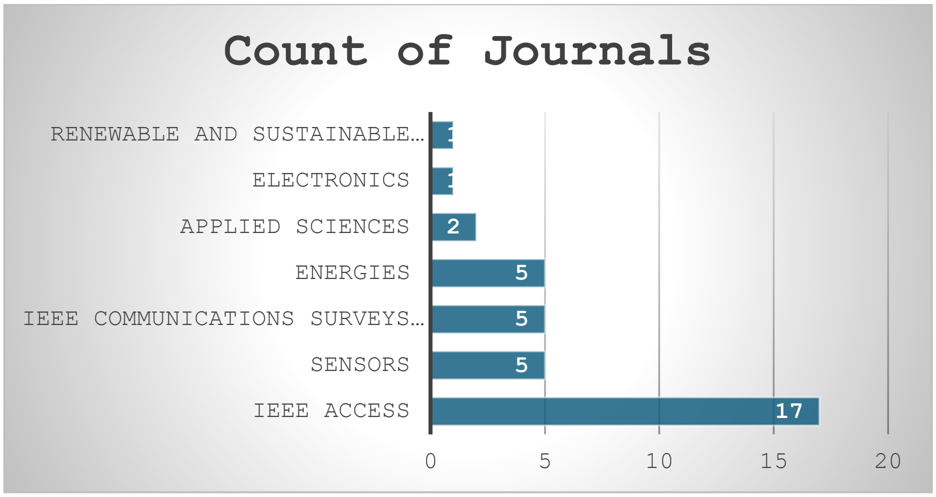

Figure 6. Distribution of MQL title-based sources

It was observed that just one journal, IEEE Access, published the maximum number of documents (17 = 47.2%). Five papers have been published in three journals each: Sensors (5 = 13.88%), IEEE Communications Surveys and Tutorial (5 = 13.88%), and Energies (5 = 13.88%); while one journal published two papers: Applied Science (2= 5.5%), and two journals published one paper each: Electronics (1=2.7%), and Renewable and Sustainable Energy Reviews (1= 2.7%).

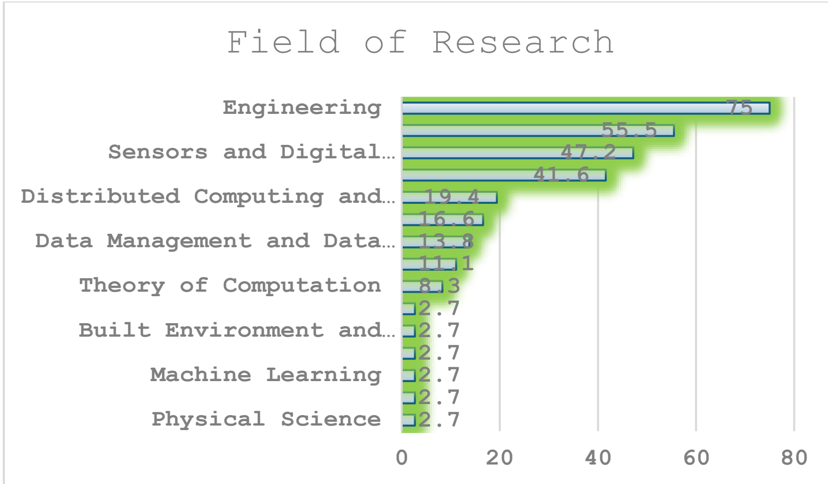

Figure 7. Distribution of the field of research

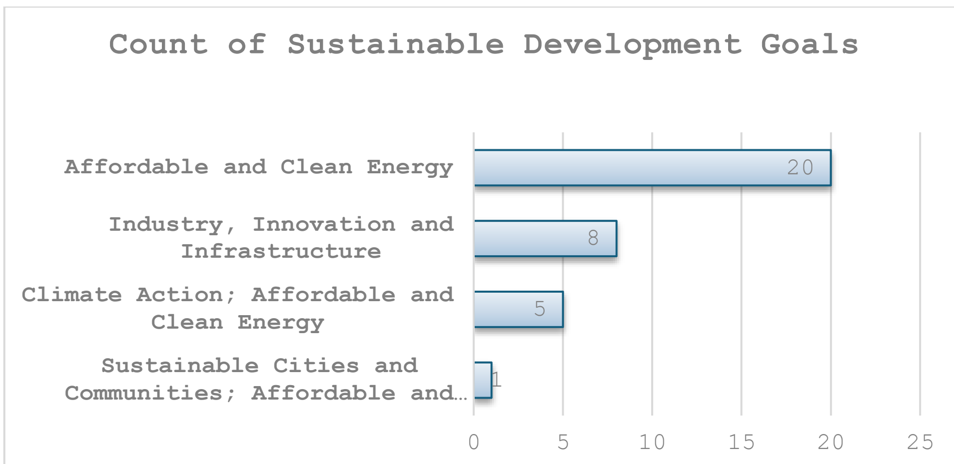

Figure 8. Articles based on the satisfaction of SDGs

Articles that belong to different fields of research and satisfy the different domain sustainability development goals (SDGs) are reflected in Figures 7 and 8. Among all the domains, QML has a wide application reflected in the field of Engineering, shown in Figure 7, while QML is mostly used in affordable and clean energy SDG-7, shown in Figure 8.

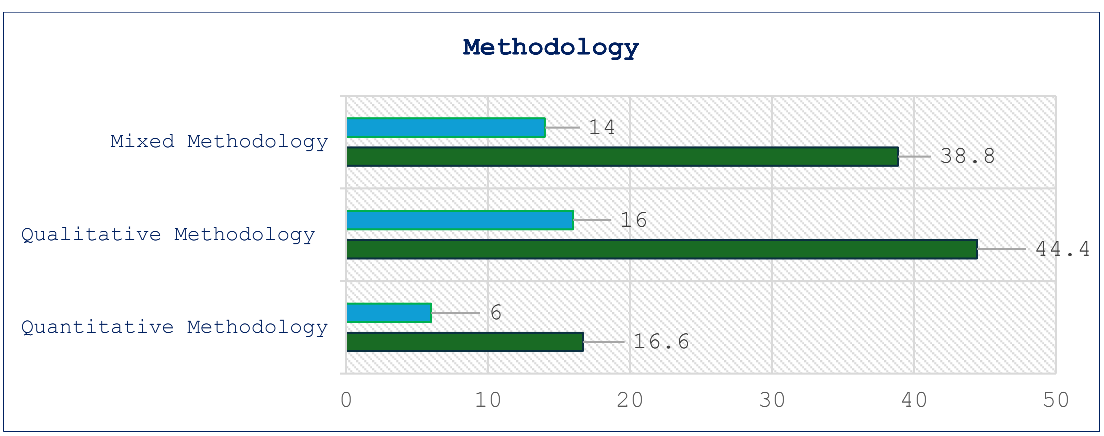

Figure 9. Articles based on methodology

3.1 Geographical distribution of the articles

The geographical distribution of scholarly articles (Figure 10) defines the country or region of origin of the research papers. This according to authors' affiliations, funding, or publishing organizations. Examining geographical distribution in your review (e.g., on Quantum Machine Learning (QML) for Industry 5.0) offers valuable insights into the international profile of research and innovation (55,56). Figure 10 demonstrates that the empirical research under consideration originated in 14 nations across several continents (Asia, Europe, the USA, and Africa). Among the 14 countries, China (8.33%), the USA (8.33%), Italy (8%), Taiwan (8.33%), India (5.54%), South Korea (5.54%), Qatar (5.54%), and the UAE (5.54%).

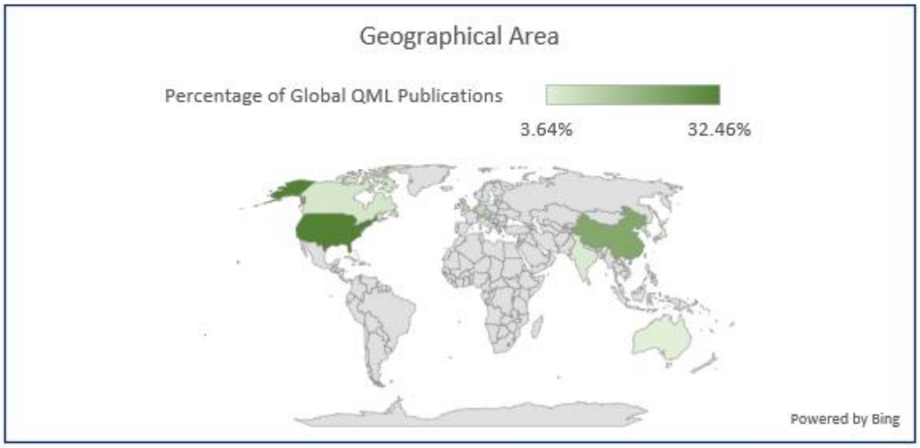

Figure 10. Geographical distribution of articles

Additionally, it should be mentioned that 18% of the research is transnational, meaning it was carried out in many countries. The remaining 37% of the research is dispersed around the world.

3.2 Thematic Map

The theme map was utilized to highlight the topic's conceptual structure based on the examination of the connections between the keywords. While centrality gauges the significance of the main theme, density gauges how well the selected theme has developed. An incredibly helpful graphic that enables us to analyze themes according to the application is called a thematic map. These nine themes served as the focal point of all the closely examined studies. Industry 5.0 is a potentially developed niche subject that is highly specialized and peripheral. Lastly, since the authors see an increasing number of reports and policies about QML-enabled industry 5.0 from nations worldwide, development policies may be identified as an emerging subject.

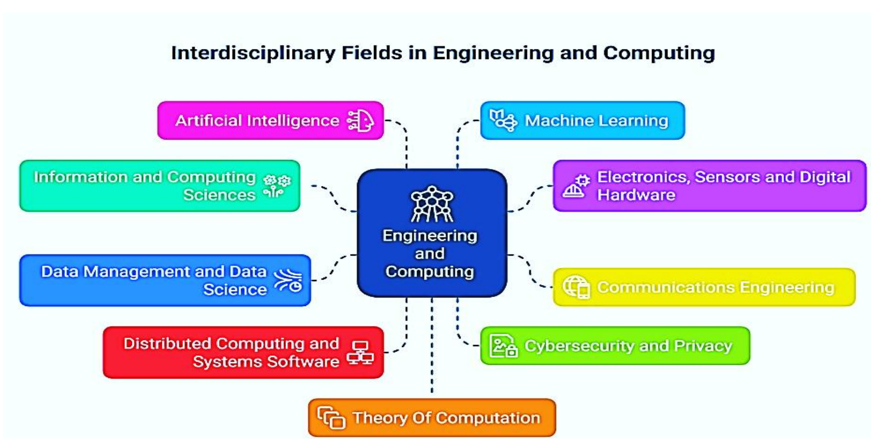

Figure 11. Thematic map of the proposed research

From the critical analysis of the literature review, it has been observed that most of the QML-enabled Industry 5.0 lies on nine interdisciplinary fields (starting from left top to right) (1) Artificial intelligence ;(2) Information and

Computing Science; (3) Data Management and Data Science; (4) distributed Computing and System Software; (5) Theory of Computation ; (6) Cybersecurity and Privacy; (7) Communication Engineering; (8) Electronics, Sensors and Digital Hardware; and (9) Machine learning shown in Figure 11.

4. Discussion

In the development of intelligent, sustainable, and human-centered industrial ecosystems, the intersection of Industry 5.0 and Quantum Machine Learning (QML) represents a turning point. Understanding the function and implications of QML becomes crucial as the world economy moves closer to Industry 5.0, which prioritizes resilience, customization, sustainability, and human-machine collaboration (31).

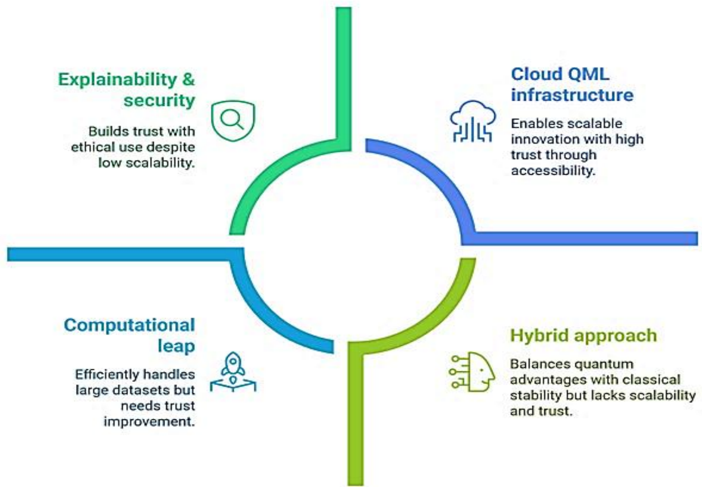

Figure 12. Insights into QML in Industry 5.0

Researchers and technologists may assess QML's disruptive potential and address the fundamental implementation issues by critically analyzing its findings. The image shows a conceptual diagram that illustrates the key components, obstacles, and potential of implementing and advancing Quantum Machine Learning (QML) in a business or industry context. The image seems to be a conceptual diagram intended to show the key components, challenges, and opportunities of implementing and advancing Quantum Machine Learning (QML) in an industrial or enterprise setting. Unlike conventional machine learning, QML leverages phenomena of quantum science such as quantum parallelism, entanglement, and superposition to engender much greater data processing, optimization, and decision-making capabilities [13,30]. These attributes are particularly crucial in the context of Industry 5.0, where there is a growing demand for intelligent human-machine cooperation, autonomous adaptability, and real-time solutions. Despite its potential, QML is still a relatively new technology, and integration into real industrial systems could result in inefficiencies, vulnerabilities, or wasted investments if the benefits, risks, and applications are not closely scrutinized and clearly understood by the industrial customers. Additionally (26,30), Examination of QML for Industry 5.0 aids in the discovery of opportunities unique to certain applications, like anomaly detection in cyber-physical systems, energy optimization in smart grids, and predictive maintenance in smart factories. In order to ensure that the use of quantum intelligence is in line with the principle of openness, inclusion, and security that underpins Industry 5.0, it also addresses ethical, explainability, and security issues [30,33]. To summarise, stakeholders could develop strategic maps, address interdisciplinary gaps in knowledge, and influence technically appropriate and socially responsible innovation by analysing the key results of QML. This is a timely yet crucial reflection for harnessing the future potential of Industry 5.0 through next-generation quantum intelligence.

4.1 Paradigm Shift Toward Human-Centric and Sustainable Intelligence

Beyond merely a technological advancement, the shift from Industry 4.0 to Industry 5.0 indicates a paradigm shift that centers industrial innovation around human values, resilience, and sustainability [39]. In Industry 5.0, a greater focus is given to promoting symbiosis. Provides greater connectivity between intelligent machines and humans than its predecessor, which focused on automation, efficiency, and digital connectivity [38,42]. In this respect, Quantum Machine Learning (QML) is the game-changer as it can give the computational intelligence to support and enable this human-centric industrial vision exhibited in Table 1.

Table 1. Insights and their impacts in Industry 5.0

Insight	Impact
Computational leap	Handles complex, large-scale industrial datasets efficiently
Hybrid approach	Balances quantum advantages with classical stability
Explainability & security	Fosters trust, ethical use, and resilience
Cloud QML infrastructure	Enables scalable, accessible quantum innovation
Aligns with Industry 5.0 ethos	Embeds human-collaborative intelligence and ethical design

By fusing cutting-edge machine learning methods with the power of quantum computing, QML opens up new possibilities for data processing, optimization, and decision-making [29]. Many times, the challenge is the ability of traditional AI systems to deal with large, high-dimensional datasets and complex decision spaces. The features like superposition and quantum parallelism offer faster and more context-aware insights to analyse such datasets more effectively, which QML achieves. In Industry 5.0, where more and more decisions in the industry are made with the help of automation, these are all essential traits. One of the key aspects of Industry 5.0 [33] is the collaborative intelligence, which involves the ability of AI systems to work in tandem with human operators, augmenting their capabilities, not replacing them. QML's ability to deal with vast streams of real-time data could enable employees to make quicker recommendations, detect anomalies, give warnings, and simulate scenarios. This enhances human-machine interaction and provides human operators who interact with intelligent systems a sense of control, assurance, and trust [31]. Explainability and trust in the use of QML are other important aspects of this paradigm. Accountability and transparency are crucial as AI systems get more intricate and are integrated into industries that depend on safety [23], like manufacturing, healthcare, and energy [34]. The ultimate aim of the recent study of Quantum Explainable AI (QXAI) is to develop tools for auditing and interpreting models based on quantum computing. This ensures regulatory compliance and promotes moral decision-making, which are crucial aspects of Industry 5.0. A second basic tenet of this new industrial era is sustainability. Some of the ways that QML can contribute to sustainability include energy-efficient computing and optimization algorithms that reduce waste, decrease energy consumption, and ensure a balance of resources. For example, QML can predict machine failure to reduce downtime and material loss, optimize smart grids, and optimize logistics in the supply chain [37]. These applications support the direct implementation of the UN Sustainable Development Goals (SDGs), to which Industry 5.0 wants to contribute. Furthermore, the QML enables mass customization, another characteristic of Industry 5.0. In sectors such as consumer goods, manufacturing, and healthcare, quantum-enhanced models can analyze biometrics, behavioural patterns, and individual preferences, without compromising on scalability and efficiency, to provide customized goods and services [40].

Quantum Machine Learning is uniquely positioned to improve human-in-the-loop systems and explainable AI in important industrial and societal applications, with special attention to safety. Classical machine learning methods, in particular, have challenges of high performance and interpretability, especially for nonlinear, high-dimensional data. QML's new computation paradigm enables a study of quantum states, probability amplitudes, and measurement results to reveal how a model reaches a specific decision. This brings new possibilities for transparency based on quantum observables and on layer-wise interpretability techniques specific to quantum circuits. Furthermore, quantum algorithms can embed human feedback more seamlessly by adaptively changing the method of measurement, or even modifying the quantum feature maps depending on the user's input, letting the user in on key moments of the model's development. An additional key contribution is the possibility of quantum decision-boundary extraction in the form of QXAI frameworks that aim to unveil meaningful, human-understandable patterns. These frameworks can, however, build quantum circuits that are already interpretable, whereby particular qubits or gates represent specific characteristics or choice elements, rather than being interpreted retroactively after the circuit has been built.

4.2 Overcoming Classical Computational Bottlenecks

The ability of Quantum Machine Learning (QML) to overcome the inherent drawbacks of classical computing in managing large, high-dimensional data environments is one of the strongest arguments for incorporating QML into Industry 5.0 [45]. Classical machine learning (ML) techniques frequently encounter bottlenecks in terms of processing speed, memory requirements, and optimization efficiency as industrial systems become more digitally connected and interconnected due to the growth of CPS. Industrial Internet of Things (IIoT) devices [22] and real-time sensor networks [38]. Utilizing the special powers of quantum physics, including quantum parallelism, entanglement, and superposition, QML provides a groundbreaking alternative to classical systems for performing calculations that are either impractical or impossible. Because quantum bits can exist in multiple states simultaneously due to superposition, QML algorithms can analyze a large number of potential solutions in parallel, as opposed to sequentially, which is the case with classical processing. Qubits may be coupled by entanglement such that, even at great distances, the state of one qubit can instantly impact the state of another. These characteristics, when combined with quantum interference, allow quantum algorithms to search and optimize vast solution spaces with previously unheard-of efficiency. Real-time optimization activities, which are crucial for Industry 5.0, benefit greatly from this exponential processing advantage. For example, QML can dynamically optimize energy consumption, machine scheduling [45], and resource allocation in a smart manufacturing facility based on quickly changing input data. In such high-velocity settings, classical algorithms could find it difficult to provide prompt replies, which could result in delays, inefficiencies, or less-than-ideal results [25]. On the other hand, QML may significantly increase operational agility and decrease decision latency. Predictive maintenance is another important use, where QML can analyze vast amounts of sensor time-series data to anticipate equipment failure before it happens. Even while traditional machine learning methods like Random Forests and Support Vector Machines have proven useful in a variety of contexts, their scalability becomes an issue as data volume and complexity rise. Faster convergence and superior generalization are provided by quantum-enhanced neural networks or quantum kernel techniques, especially when integrated into high-dimensional feature spaces. Likewise, cyber-physical systems (CPS) require high-speed anomaly detection to protect industrial processes from malfunctions, cyberattacks, or safety risks. Quantum k-Means clustering and Quantum Boltzmann Machines are two examples of QML algorithms that are more effective at classifying patterns and identifying deviations in real time [28]. This capability is crucial for Industry 5.0 applications, where safety, resilience, and autonomy play vital roles, especially in energy systems, autonomous transport, and healthcare.

Unlike classical methods, Quantum Machine Learning can make use of a number of properties that classical computation cannot, such as superposition, entanglement, and interference. The phenomena can be used to achieve theoretical exponential or near-exponential improvements in certain problem classes by searching a very large search space in parallel using quantum systems. In optimization problems, where numerous industrial problems can be found, quantum algorithms like the Quantum Approximate Optimization Algorithm (QAOA) and quantum-enhanced gradient descent approaches may evaluate several possible paths to the solution at once. This decreases the time to obtain high-quality solutions to combinatorial problems, which are often difficult to solve using traditional algorithms, especially for problems with complex dimensionality and constraint structure. The scalability feature is another unique benefit. With the rapidly growing industrial data that includes high-resolution sensor data, multimodal IIoT streams, and large-scale simulations, the classical modelling approach inevitably has significant limitations. By contrast, quantum circuits can efficiently store data in compact quantum states that contain high-dimensional information, which can be manipulated efficiently by processing data that is otherwise too cumbersome. This ability is especially useful when the optimization landscape has a large number of local minima or variables that interact in a non-linear manner, necessitating non-linear modelling. To overcome these bottlenecks, the ability to evaluate these interactions in a single "parallel" computational step is provided by quantum parallelism.

4.3 Integration into Cyber-Physical and Intelligent IIoT Systems

The technical foundation of Industry 5.0 is made up of CPS [15] and the Industrial Internet of Things (IIoT) (24), which allow digital intelligence and physical machines to work together seamlessly. These systems use sensors, actuators, controllers, and embedded devices to produce enormous amounts of high-dimensional, real-time data. For traditional machine learning (ML) systems, handling and extracting useful insights from such data is extremely difficult, particularly when latency, scalability, and reliability are limited. A possible answer to these problems is provided by quantum machine learning (QML), which opens up new avenues for adaptive control, predictive analytics, and intelligent automation. The capacity of QML to conduct scalable, noise-resilient analytics is among its most important contributions to IIoT systems. In contrast to traditional machine learning, QML algorithms can effectively evaluate large, multidimensional data streams by utilizing quantum features like superposition and quantum entanglement. Even in noisy industrial settings where conventional techniques frequently fail, this capacity enables real-time anomaly detection, failure prediction, and pattern identification at previously unheard-of rates. For instance, sparse and unbalanced datasets, which are typical in sensor-driven applications, are better handled by quantum-enhanced neural networks and quantum support vector machines. The development of quantum-enhanced federated learning is another important breakthrough. Data is dispersed across many edge devices in IIoT networks, from sensors to intelligent robots, each of which gathers local data. These devices can work together to train models without exchanging raw data, thanks to federated learning, protecting privacy and using less bandwidth. Federated learning is very effective for privacy-aware, decentralized intelligence as it can take advantage of quantum speed-ups in optimization and model convergence when combined with QML. This is especially helpful in fields where data sensitivity and reactivity are critical, such as healthcare, smart grids, and driverless cars. Additionally, distributed QML architectures are being created to help edge-cloud collaboration in intelligent manufacturing systems and smart factories. In such environments, genuine quantum processors or quantum simulators may perform more complicated calculations in the cloud, while lightweight quantum-inspired models can process time-sensitive activities like robotic coordination or equipment monitoring near the edge. New techniques such as quantum kernel techniques, variational quantum circuits, and others are being explored for hybrid edge-cloud systems.

QML, combined with Industrial Internet of Things (IIoT) and cyber-physical systems (CPS), offers a distinctive chance to improve adaptive, decentralised, and real-time intelligence. Distributed sensor networks, autonomous devices, and digital controllers are becoming key components of industrial ecosystems, where they must rapidly sense dynamic environments and respond accordingly with minimal delay. Classical models are challenged by the need to achieve high accuracy, real-time response, and limited computing resources at the edge. New approaches to these limitations can be found in quantum-enhanced learning, where the quantum bits would enable learning the complex relationships across sensor streams that are too costly to compute classically. One of the key advantages of decentralized control is the ability of quantum systems to efficiently represent and update multi-variable dependencies. Rapid inference and adaptive control signals can be generated through hybrid loops in edge-assisted quantum cloud environments using QML models. This enables CPS frameworks to adapt better to changing environments, machine-to-machine interactions, and unforeseen operating modes. Another benefit is the ability to identify minute variations, or unusual system patterns, that could be missed by traditional models because of noise, combinatorial complexity, or noise in the continuous data.

4.4 Quantum-Aware Data Analytics and Decision Support

The need for sophisticated analytics and responsive decision support systems is growing rapidly in the context of Industry 5.0, where decision-making must strike a balance between speed, accuracy, human cooperation, and sustainability. Even while they work well in many situations, traditional decision-support technologies sometimes struggle to handle high-dimensional data, non-linear relationships, or real-time limitations. By providing quantum-aware data analytics that can be immediately integrated into industrial decision-making platforms, Quantum Machine Learning (QML) provides a revolutionary improvement over existing systems. The integration of hybrid QML models into operational control systems and analytics dashboards is known as quantum-aware decision support. The benefits of both conventional and quantum computing are combined in these hybrid architectures [17]. In computationally demanding jobs, quantum modules are utilized for optimization, pattern recognition, or probabilistic inference, while classical components manage standard data processing and user interface operations. For human-in-the-loop systems, in which operators supervise or co-direct autonomous operations, this configuration is perfect. The ability of QML-enhanced decision support systems to provide real-time control is among their most alluring features. Complex optimization problems may be solved much more quickly by quantum algorithms like the Variational Quantum Eigensolver (VQE) and the Quantum Approximate Optimization Algorithm (QAOA) than by traditional heuristics. QML systems may produce high-quality solutions in a condensed computational window in situations where prompt answers are essential, such as manufacturing line scheduling, energy distribution, and robotic route planning. Additionally, QML makes multi-objective optimization possible, which is essential in Industry 5.0 as choices must take into account a number of competing objectives, including safety, cost, quality, and energy efficiency. Because of quantum parallelism and entanglement, quantum-enhanced models are able to investigate Pareto-optimal solutions more quickly and completely than conventional approaches. Decision-makers can use these skills to dynamically weigh trade-offs in response to stakeholder input, regulatory limitations, and changing real-time situations. In HRL decision systems, QML is a key component in complementing human intelligence. Operators can use decision dashboards, which integrate QML to visualize solution spaces, identify potential risks or anomalies, and provide probabilistic forecasts, to make informed decisions. This is complemented by the addition of Quantum Explainable AI (QXAI) modules [5] that play a vital part in enhancing confidence and ensuring accountability in high-stakes industrial applications by trying to provide transparency and interpretability of quantum-inspired suggestions. Additionally, quantum-enabled analytics aids businesses in transitioning from a reactive to a proactive decision-making process. For instance, QML can forecast supply chain management problems brought on by inclement weather, shifting demand, or logistical issues, enabling prompt responses. QML can forecast peak loads in a smart energy network or optimise the storage of energy in a battery, thus improving the operational resilience and sustainability of the network. Another exciting potential space would be the integration of QML with digital twin technology, where real-time decision support systems are driven by quantum-enhanced simulations. This reduces the likelihood of risk and enhances outcomes by allowing managers to test and assess virtual treatments prior to putting them into practice on real assets.

4.5 Application Domains in Industry 5.0

Numerous industrial and societal fields might undergo radical change if Quantum Machine Learning (QML) is included in Industry 5.0. Industry 5.0, with innovation focused on humanization, sustainability, and resilience, requires computational solutions that can handle complex tasks, make real-time decisions, and adapt to the changing environment [23]. With its quantum-enhanced learning and data processing capabilities, QML provides revolutionary benefits in a variety of industries.

4.6 Smart Manufacturing:

Predictive maintenance and adaptive quality control are essential in smart manufacturing to reduce waste, prevent downtime, and guarantee constant product quality. Compared to classical machine learning, QML can more accurately identify abnormalities or deviations in product standards by analyzing massive amounts of sensor data in real time. For example, preventive maintenance scheduling is made possible by quantum-enhanced time series forecasting models, which can identify when a machine is going to break [9–11,31]. A key component of Industry 5.0, this improves overall equipment effectiveness (OEE) and guarantees more seamless human-machine cooperation on the manufacturing floor.

Current demonstrations are limited to examples that are controlled within a laboratory and quantum simulators. These limited-scale experiments demonstrate that either quantum kernel algorithms or variational circuits may be trained to identify anomalies in simplified representations or forecast vibration signatures under a noise-free setting. Although such proofs-of-concept can prove useful, they cannot yet show any scaling of size, variability, or streaming demands of realistic manufacturing conditions. To date, no factory has reported any quantifiable improvements in predictive accuracy or reduction in downtimes when using QML. Due to qubit noise, depth of circuit noise, and available memory, real-time data streams of factory data are beyond the capabilities of devices of the NISQ era. LSTM, CNNs, or hybrid transformer models of classical ML are more reliable, scalable, and can be deployed than QML.

4.7 Energy Systems:

Grid stability in contemporary energy systems, especially those that use renewable energy sources, depends on effective load balancing and forecasting. Quantum machine learning (QML), particularly in the form of quantum neural networks (QNNs), can optimize the distribution of energy across varied inputs, such as wind and solar [29-30]. Better energy storage management and dynamic demand-response methods are made possible by these models' increased ability to predict variations in energy generation. Additionally, QML may be utilized to improve smart microgrid layouts, resulting in more robust and environmentally friendly energy infrastructure that supports Industry 5.0's sustainability objectives. The existing validations are mostly simulated. Small-scale optimizations to renewable predictions, or hypothetical optimizations of microgrids, as studied, demonstrate how the model works under perfected, no-noise conditions without being in any way representative of the effort scale of a real-world energy infrastructure. Grid scale forecasting requires real-time, high-dimensional, stable, and high-dimensional optimization, which, as of today, cannot be performed by current quantum hardware. QML cannot be deployed on operational grid systems due to noise, decoherence, and a small number of qubits. Classic forecasting models, particularly hybrid deep-learning and physics-informed models, are still much more accurate and reliable.

4.8 Autonomous Systems:

Drones, industrial robots, and autonomous cars are examples of autonomous systems that mainly depend on perception, sensor fusion, and real-time decision-making. By effectively processing high-dimensional sensory input (such as LiDAR, radar, and image data) and discovering patterns that allow for context-aware decision-making, QML improves these capabilities. Autonomous systems can navigate complicated surroundings, avoid obstacles, and adapt to new tasks with little assistance from humans [13,33]. These developments help realize Industry 5.0's goal of intelligent and safe human-machine collaboration. To date, all computations are conceptual and confirmed by low-dimensional simulations. Quantum classifiers have been demonstrated to work on simplified obstacle-detection tasks, and QRL agents have been able to navigate in small grid worlds. All these presentations fall short of the latency or robustness specifications of autonomous robotics in the real world. Likely Solutions. Although it is beyond the current quantum processors to implement inference in milliseconds and high-resolution sensor processing, this type of aspect is what autonomous systems require. Most high-dimensional sensors, like LiDAR, radar, and camera sensors, cannot be dealt with by the QML models. Until quantum hardware can implement more complicated circuits and achieve reduced noise levels, real-time deployment is not achievable.

4.9 Healthcare and Bioinformatics:

QML has enormous potential for the healthcare industry, especially in the areas of genomics, precision diagnostics, and customized treatment. Quantum models can more effectively forecast disease risk, detect mutations, and speed up the examination of genetic sequences. For instance, QML can help with early diagnosis and therapy customization by enabling quicker pattern detection in huge biological datasets. Additionally, by simulating molecular interactions at the quantum level, quantum-enhanced drug discovery platforms can significantly cut down on the time and expense required to create novel treatments. This is in line with Industry 5.0's objective of providing accessible, moral, and individualized healthcare solutions. Industry 5.0's use of quantum machine learning is not limited to any one industry; rather, it is a cross-cutting enabler that promotes creativity, effectiveness, and human-centeredness across a variety of fields. QML is at the forefront of the next industrial revolution, from energy sustainability, autonomous decision-making, and customized healthcare to predictive intelligence in manufacturing. It is crucial for enterprises hoping to take the lead in the era of intelligent, accountable, and adaptable technology because of its capacity to analyze large amounts of complicated data at previously unheard-of speeds. Some quantum models are observed to improve on toy genomic data and problems in molecular chemistry. Small molecules have been simulated by variational quantum algorithms, and quantum classifiers have been used on a limited variety of biomedical data. Nevertheless, the majority of such demonstrations are academic, as opposed to clinical validation. Limiting Factors Nowadays, the volume of qubit storage is surpassed by the size of certain industrial-scale genomic datasets. Drug discoveries involve heavy circuits and fault tolerance that is not available in current NISQ devices. The majority of ethical considerations, such as explainability, auditability, and amplification of bias, are still not fully resolved, and hence, clinical integration is still in its infancy.

4.10 Strategic Impact:

In the context of Industry 5.0, Quantum Machine Learning (QML) is more than just a computational development; it is the introduction of a new industrial intelligence layer that reinterprets the relationships between economic infrastructure, human involvement, and cyber-physical systems (CPS). QML can revolutionize not only processing speed and efficiency but also how institutions, countries, and businesses function, develop, and compete. Fundamentally, QML combines machine learning with quantum computing concepts to enable previously unheard-of levels of efficiency in pattern identification, classification, and decision-making in intricate, high-dimensional data environments (24). Applying QML to Industry 5.0, a paradigm that prioritizes customized manufacturing, human-machine cooperation, resilience, and sustainability, makes it the link that strengthens real-time intelligence across systems. From smart healthcare and transportation logistics to factory optimization and energy distribution, this quantum-enhanced intelligence can coordinate choices across a wide range of areas. When national competitiveness is taken into account, the strategic influence of QML is most noticeable. QML integration will be a crucial technical differentiation as companies compete to digitize, automate, and decarbonize [2]. Investing in QML skills will provide nations with a major advantage in creating innovation ecosystems, energy networks, and supply chains that are more efficient. QML is positioned to play a key role in forming the knowledge economy of Industry 5.0, just like AI and cloud computing transformed Industry 4.0. Additionally, QML enables industrial infrastructure to be more robust and adaptive, particularly when addressing dynamic global challenges such as labor shifts, supply chain disruptions, and climate change. Models with quantum enhancements can predict disruptions, optimize multi-objective trade-offs, and recommend preventative measures [14-15,33]. Organizations can react quickly to shifting market and environmental situations thanks to this capacity, which also increases decision agility and operational effectiveness. Human-centricity is another dimension of strategic value. In Industry 5.0, QML systems may be built to function inside human-in-the-loop designs, in contrast to completely automated systems that minimize human input. This guarantees that decisions are still open, inclusive, and morally sound. QML thereby reaffirms Industry 5.0's dedication to technology that empowers rather than replaces humans. Various reviewed papers point to growing institutional and industrial investment in QML through national programs, cloud-based quantum pilots, and collaborative research networks. In addition to generating employment and intellectual property, countries that engage in quantum R&D, develop quantum education pipelines, and encourage industrial adoption will also influence international norms and partnerships in automation and manufacturing for the quantum era [12,30]. Early adopters of QML are expected to benefit from first-mover advantages, such as improved product customization, reduced operating costs, and process improvements.

Higher profits, improved market positioning, and long-term sustainability are the results of these advantages. Customer expectations in industries like autonomous mobility, smart infrastructure, and precision healthcare will be redefined by QML-enabled goods and services, especially those that make use of intelligent prediction, personalization, or optimization.

5. Challenges and Roadblocks

It is not obvious whether QML can actually perform better than the classical methods, especially taking into account the existing hardware, cost, and complexity of hardware and software developments. When quantum machine learning is compared to standard classical algorithms associated with quantum machine learning, it becomes clear that the advantages of quantum machine learning remain, to date, theory-driven and need verification in practice in real-world industries. To do bolstering, prognosticating, line identification, and irregularity detection, even current classical models can work perfectly on modern high-performance computer systems and yield good and dependable results at a comparatively low cost. It is against this backdrop that QML is expected to give faster computations to some problem classes and explore a very large state space. Such benefits, however, depend on mature, fault-tolerant quantum hardware, which is not yet in existence. The current NISQ-era quantum devices are, in comparison, noisy and have a small number of qubits and errorful circuits, thus often rendering null the theoretical speedups of academic contributions. In most of the applications that are described here, like intelligent manufacturing, predictive maintenance, or resource optimization, it is not known whether QML is actually doing better than well-designed classical algorithms runnable on traditional processors or GPUs. Moreover, quantum systems are more expensive to implement in terms of finances and operational expenses, unlike the case with classical ML pipelines. As a result, the real performance difference between QML and classical approaches remains ambiguous, and quantum hardware will need to be developed further before classical machine learning, which is applied to the majority of Industry 5.0 tasks, becomes infeasible and unreliable. While Quantum Machine Learning (QML) holds immense promise for transforming Industry 5.0, its practical realization is still constrained by several critical challenges. These barriers range from limitations in hardware and algorithm accessibility to the preparedness of the workforce and ethical concerns. These barriers must be understood and addressed with a nuanced understanding in order to facilitate responsible innovation and successful integration of QML in human-centric sustainable industrial ecosystems.

6. Conclusion

By taking into account a methodical and critical evaluation of the articles, the suggested survey offers readers helpful insights into the function of QML as a possible facilitator to inspire trust in Industry 5.0 in the following dimensions.

- QML supports human-in-the-loop collaboration and explainable AI (QXAI), ensuring transparency, trust, and ethical AI deployment.
- QML delivers exponential gains in processing speed, optimization, and scalability by leveraging quantum phenomena like superposition and entanglement.
- QML enhances IIoT and CPS operations through real-time analytics, adaptive control, and quantum-enhanced learning for decentralized intelligence.
- QML improves predictive maintenance, energy optimization, and personalized healthcare through efficient analysis of complex industrial datasets.
- QML fosters sustainable industrial innovation and strengthens global competitiveness through energy-efficient quantum-driven intelligence.

Conflicts of Interest:

The authors declare no conflicts of interest.

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