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Quantum machine learning a new frontier in smart manufacturing: a systematic literature review from period 1995 to 2021

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ABSTRACT
Quantum machine learning can play an essential role in smart manufacturing applications. This paper aimed to understand the state of the art of quantum computing in machine learning and its role in smart manufacturing. A systematic literature review of 45 articles from 34 reputed journals from 1995–2021 was carried out. The study grouped documents into different categories and sub-categories for detailed analysis. The four broad categories, namely quantum neural network, quantum regression, quantum clustering, and quantum for smart manufacturing technologies, were studied. However, the analysis revealed that most studies belonged to the quantum neural network. Quantum for smart manufacturing is gaining the attention of researchers and practitioners, and developed countries such as the USA and China are leading towards the implementation of quantum machine learning for smart manufacturing. This study proposed a framework of quantum-integrated smart manufacturing and specified significant research gaps for future trends and directions. Also, valuable insights into quantum machine learning and its adoption for smart manufacturing have been offered.

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KEYWORDS
Smart manufacturing; quantum computing (QC); quantum clustering; quantum machine learning (QML); quantum neural network (QNN); quantum regression

1. Introduction

Quantum computing (QC) has become a reality in which machines utilize quantum phenomena to solve mathematical problems which are challenging to solve with conventional computers, such as quantum entanglement, and quantum superposition (Grimsley et al. 2019). The quantum machine performs calculations based on quantum laws, i.e. subatomic particle behaviour (Figgatt et al. 2019). Large-scale quantum computers perform many impossible things for a classical computer (Johri, Steiger, and Troyer 2017). QC is being used in various application domains such as chemistry (Yuan 2020), intelligent systems (Chen et al. 2020), cyber security (Wiebe and Kumar 2018), 5 G/6 G network (Chamola et al. 2021), and finance (Akhtar et al. 2020). A primary motivation of QC was the impending end of Moore's law (Powell 2008). In the last five years, North American and Asian companies have worked more prominently on QC patents (MacQuarrie et al. 2020). Established and start-up companies have been working on software and hardware aspects of QC. Major established companies operating in QC are as follows: Alibaba, Hitachi, Toshiba, HP, Google, Microsoft, Intel, and IBM (O'Quinn and Mao 2020a). Start-up firms such as IonQ, 1QBit, PsiQuantum, Rigetti, D-Wave Systems, etc., are developing commercial quantum platforms (O'Quinn and Mao 2020a). Researchers across the globe are proposing artificial intelligence (AI) based technologies for QC (O'Quinn and Mao 2020b). Machine learning-based quantum systems, often referred to as Quantum Machine Learning (QML), has emerged as a prime research field (Schuld, Sinayskiy, and Petruccione 2015).

Classical QML methods are boosting, regression, support vector machine (SVM), neural networks, principal components, etc (Wittek 2014). The physical realization of these QML methods is under process. Initially, the boosting and neural network methods were implemented successfully (Dunjko, Taylor, and Briegel 2016). Perceptron is a fundamental building block of an artificial neural network (ANN). Moreover, the quantum perceptron is a building block for QML with an ability of QC such as machine learning (ML)

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schemes, entanglement, and state supervision (Ban et al. 2021). Thus, a quantum neural network (QNN) has been discussed in the literature as an initial step of QML. Some of the QNN applications discussed in the literature are as follows: predicting time series (Cui, Shi, and Wang 2015), stability enrichment of power structure (Ganjefar, Tofighi, and Karami 2015), robotics (Gonçalves 2018; Yun et al. 2023), and retrieval of target pattern (Osakabe et al. 2021).

In ML, patterns are learned/derived from the input-output data, and it primarily focuses on clustering and pattern classification (Dang et al. 2018; Oroojlooyjadid, Snyder, and Takáč 2020). In addition, QML in ML can calculate classical distances, explore quantum models, and reformulate the language of open QC systems (Schuld, Sinayskiy, and Petruccione 2015). Some of the QML applications discussed in the literature are as follows: 5 G/6 G (Akhtar et al. 2020), intrusion detection (Chen et al. 2020), image classification (Dang et al. 2018), high energy physics (Guan et al. 2020), reaction prediction (Kang and Liu 2020), feature extraction (Li et al. 2020), predicting molecular energy (Reddy and Bhattacherjee 2021). Recent studies discusses QML for material manufacturing (Collantes et al. 2023; Glavin, Ajayan, and Kar 2023), anamoly detection (Ha et al. 2023), renewable energy (Epps et al. 2023; Karimaghaei et al. 2023), and graph photonics (Bao et al. 2023).

The research in QML is in the developing phase. Only three literature survey articles in peer-reviewed journals were identified. Nevertheless, researchers and academicians have plenty of opportunities to conduct substantial research in this domain.

Pande and Mulay (2020) conducted a bibliometric survey of QML in which 430 research articles from the period 2014–2019 from Web of Science and Scopus databases were analyzed to identify prominent journals, authors, and institutions. Deshmukh and Mulay (2021) performed patent and bibliometric analysis.

It may be noted that quantum computing can redefine and disrupt manufacturing by developing breakthrough services and products. The optimization of processes, development of products, and discovery of chemicals are amongst the areas of manufacturing that are expected to undergo significant innovations with QC. The uses cases in manufacturing may be categorized into four segments, namely 'Supply' which focuses on risk modelling and optimization of the supply chain; 'Control' which covers classification, ML, and optimization; 'Discover' takes into account chemistry, material science, and condensed matter physics; Lastly, 'Design' which covers hydro/aerodynamics, structural analysis, and finite difference analysis (Malina and Woerner 2019). The QC can help manufacturers in reducing the costs of the products without compromising the system's performance. Using ML with QC would increase the optimization runs and help in evaluating added interactive processes and factors for improving productivity (van Erp and Gładysz 2022).

In the context of logistics and supply chain, QC could improve decision-making, reduce lost sales, decrease operational costs, vendor order optimization, fortify cybersecurity, analyse software performance, etc. It is a quality addition to the concepts of Industry 4.0. Further, the QC could offer safe, more streamlined processes and enhance every aspect right from the design stage to quality control (Malina and Woerner 2019; van Erp and Gładysz 2022). Hence, there is a significant need to explore the status and role of QC in the manufacturing domain.

It may be noted that publications of QML in Computer Science, Astronomy, and Physics were prominent. However, these studies failed to address the comparative analysis of the themes and categories of QML. A detailed understanding of themes and categories will ensure a holistic performance of QML's recent developments for smart manufacturing. Furthermore, future research directions can be identified based on these categories. The research questions that this review study aims to address are:

RQ1: What are the themes for the QML as indicated in the literature?

RQ2: What is the state of the art in the context of QML and manufacturing

RQ3: How to achieve QML-integrated smart manufacturing

By addressing the following research objectives (ROs) have been achieved in this study.

RO1: To identify several themes and categories in the context of QML by reviewing the research articles.

RO2: To explore the role of QML in the manufacturing domain.

RO3: To propose a framework for QML-integrated manufacturing which leads to smart manufacturing.

The manuscript is structured as follows: Section 2 gives the adopted methodology for the study. Then, themes and categories are discussed in section 3. Next, section 4 elaborates on the findings and discussion. Finally, the conclusion of the study is given in Section 5.

2. Methodology

A systematic literature review (SLR) approach is used to analyze the research objectives. SLR is popularly used to understand a particular research domain's state of the art. Tranfield et al. (2003) emphasized the importance of SLR for evidence-based research. Deciding on keywords for search and shortlisting the articles is the most significant step in SLR. Vieira and Kumar (2004) highlighted the importance of keyword finalization in SLR and the TAK (Title- Abstract-Keyword) principle for shortlisting the articles. Munn et al. (2018) compared the performance of SLR with scoping reviews and traditional literature reviews. The study finds that SLA performs better compared to scoping reviews and traditional literature reviews on the following parameters: i) Synthesis of research findings from several studies and creation of 'summary' research findings; ii) Assessment of Bias; and iii) A priori assessment protocol. The methodology adopted for SLR is shown in Figure 1.

2.1. Phase I: planning

Before starting the SLR, a panel of experts having considerable knowledge and experience in the QC domain was formed. The committee is comprised of nine experts from academia and industry. Four academic experts (one each from Computer Science, Information Technology, Electronics, and Physics), two industry experts from AI/ML domain, two data analysts, and one Research and Development (R & D)

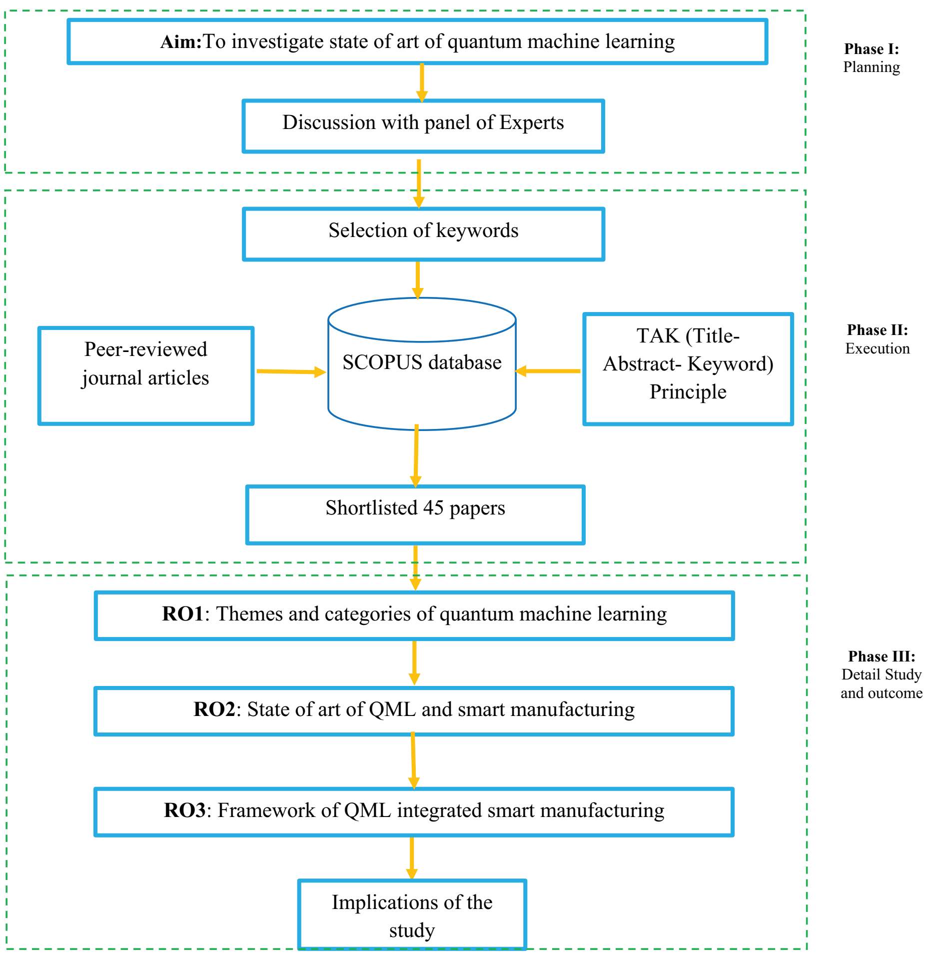

Figure 1. Methodology adopted for SLR.

Table 1. Article selection criteria.

Inclusion criteria	Exclusion criteria
Articles from the Scopus database	Articles from other databases
English language articles	Other languages except for English
Peer-reviewed journal articles	White papers, technical/working papers, reports, textbooks, doctoral dissertations, master's thesis, conference papers, and online sites
Articles with Quantum Computing, Artificial Intelligence, Machine Learning, Intelligent Systems, Smart Manufacturing	Articles with Chemistry, Evolutionary Algorithms, Genetic Algorithms, Optimization

person were contacted to finalize the exclusion and inclusion criteria. The search database, list of keywords, and review protocol were finalized in consultation with the experts' panel (Hu et al. 2015). Table 1 shows the criteria of inclusion and exclusion for the SLR.

2.2. Phase II: execution

Search strings were created based on keywords identified in the first phase to identify the research articles. A few examples of search strings are as follows: 'Quantum computing' AND 'Artificial intelligence', 'Quantum computing' AND 'Machine learning', 'Quantum computing' AND 'Intelligent systems', 'Quantum computing' AND 'Cybersecurity', 'Quantum computing' AND 'Smart Manufacturing', etc. These combinations were searched in the Scopus database on 2 April 2021. Scopus database offers twenty percent more articles than Web of Science (Falagas et al. 2008). Thus, Scopus was selected for the search, and it was carried out without mentioning the starting year to get the maximum number of articles. We gathered 330 articles from 1984 to 2021, including journals, conference proceedings, book chapters, white papers, etc. According to Ordanini et al. (2008), only peer-reviewed research articles should be considered helpful knowledge. Hence, only peer-reviewed articles were considered for further study in the initial screening. As a result, the total number of peer-reviewed research articles identified was 124. In SLR, the TAK principle is commonly used to finalize the papers for detailed study (Chechurin 2016; Maroli, Narwane, and Gardas 2021; Shah et al. 2021; Thavi et al. 2021; Vieira and Kumar 2004). Therefore, we applied the TAK principle to 124 journal articles and removed irrelevant articles after screening each article. As a result, only 45 articles focusing on Quantum computing in AI and ML application domains were selected for the detailed study. Table 2 shows the list of selected papers (sorted by year of publication).

2.3. Phase III: detailed study and outcome

A detailed Excel sheet of 45 articles has been developed to get a clear picture of the categories. Further, each article's detailed report was made based on the introduction, methodology, results, and conclusion. Finally, the panel of experts assessed the completeness and scientific quality of the report, whose main aspects are given in the next section: Themes and Categories.

3. Themes and categories

This part of the paper addresses the first research objective (RO1) – 'To identify themes and categories discussed in the literature for QML'.

3.1. Categories of papers

Based on the type of papers in Table 1, the documents were divided into Literature review (LR), General review (GR), Conceptual paper (CP), Viewpoint (VP), Research paper (RP), and Case study (CS). To understand research in QML, Deshmukh and Mulay (2021) analyzed innovations in quantum clustering using bibliometric analysis. The study also examined patents in QML and concluded the popularity of QML in physics, astronomy, and computer science. Pande and Mulay (2020) performed a bibliometric analysis and compared Scopus and Web of Science data. The study identified the top ten research journals, authors, and institutes in QML. GRs were prevalent in this domain, and the following authors analyzed QML through the GR: Chamola et al. (2021), Coveney and Highfield (2020), Dunjko and Briegel

Table 2. Shortlisted articles for SLR.

S. N	Authors	Year of publication	Country of the first author	Targeted Domain/Industry	Type of paper
1	Acampora and Schiattarella	2021	Italy	Manufacturing	Research paper
2	Ban et al.	2021	Pakistan	General	Case study
3	Chamola et al.	2021	India	Service	General review
4	Date et al.	2021	USA	General	Research paper
5	Deshmukh and Mulay	2021	India	General	Literature review
6	Li et al.	2021	USA	Healthcare	Case study
7	Liu et al.	2021	China	Manufacturing	Research paper
8	Osakabe et al.	2021	Japan	Manufacturing	Research paper
9	Reddy and Bhattacharjee	2021	India	General	Research paper
10	Sharma et al.	2021	India	Manufacturing	Research paper
11	Akhtar et al.	2020	Pakistan	Service	Conceptual paper
12	Chen et al.	2020b	China	Manufacturing	Research paper
13	Coveney and Highfield	2020	UK	Manufacturing	General review
14	Li et al.	2020	China	Healthcare	Research paper
15	Pande and Mulay	2020	India	General	Literature review
16	Peyton et al.	2020	USA	Manufacturing	Research paper
17	Tacchino et al.	2020	Italy	Manufacturing	Research paper
18	Taylor	2020	USA	General	Viewpoint
19	Villmann et al.	2020	Germany	Manufacturing	Research paper
20	Bhatia et al.	2019	India	General	Research paper
21	Havlíček et al.	2019	USA	Manufacturing	Research paper
22	Miller	2019	UK	General	Viewpoint
23	Nguyen et al.	2019	USA	Service	Research paper
24	Biamonte et al.	2018	Russia	General	Conceptual paper
25	Dang et al.	2018	China	Manufacturing	Research paper
26	Dunjko and Briegel	2018	Austria	General	General review
27	Gao et al.	2018	China	General	Research paper
28	Gonçalves	2018	Portugal	Manufacturing	Case study
29	Moret-Bonillo	2018	Spain	General	General review
30	Wiebe and Kumar	2018	Canada	Manufacturing	Research paper
31	Zwolak et al.	2018	USA	Manufacturing	Research paper
32	Benedetti et al.	2017	USA	Manufacturing	Research paper
33	Fingerhuth et al.	2017	Canada	General	General review
34	Fujii and Nakajima	2017	Japan	Manufacturing	Research paper
35	Kieferová, and Wiebe	2017	Canada	Manufacturing	Research paper
36	da Silva et al.	2016a	Brazil	General	Research paper
37	da Silva et al.	2016b	Brazil	General	Research paper
38	Cui et al.	2015	China	Manufacturing	Research paper
39	Ganjefar et al.	2015	Iran	Manufacturing	Research paper
40	Moret-Bonillo	2015	Spain	General	General review
41	Schuld et al.	2015	South Africa	General	General review
42	Li et al.	2013	China	General	Research paper
43	Liu et al.	2013	Taiwan	General	Research paper
44	Panella and Martinelli	2008	Italy	General	Research paper
45	Kak	1995	USA	General	General review

(2018), Moret-Bonillo (2018), Fingerhuth et al. (2018), Moret-Bonillo (2015), Schuld et al. (2015), and Kak (1995). Discussion on other types of papers is as follows:

Kak (1995) deliberated on QNN for basic perceptron considering uncertainty. It is the first time quantum for a neural network was discussed. Moret-Bonillo (2015) studied the benefits of AI/ML for QC and analyzed the situation in 2014 through efforts taken by Google, NASA, Bell Labs, and IBM. Schuld et al. (2015) investigated how QC helps in improving ML algorithms and focused on unsupervised and supervised learning for clustering and classification. Fingerhuth et al. (2018) discussed QML with key application policies and improved control. To understand recent progress in AI/ML in the QC, Dunjko and

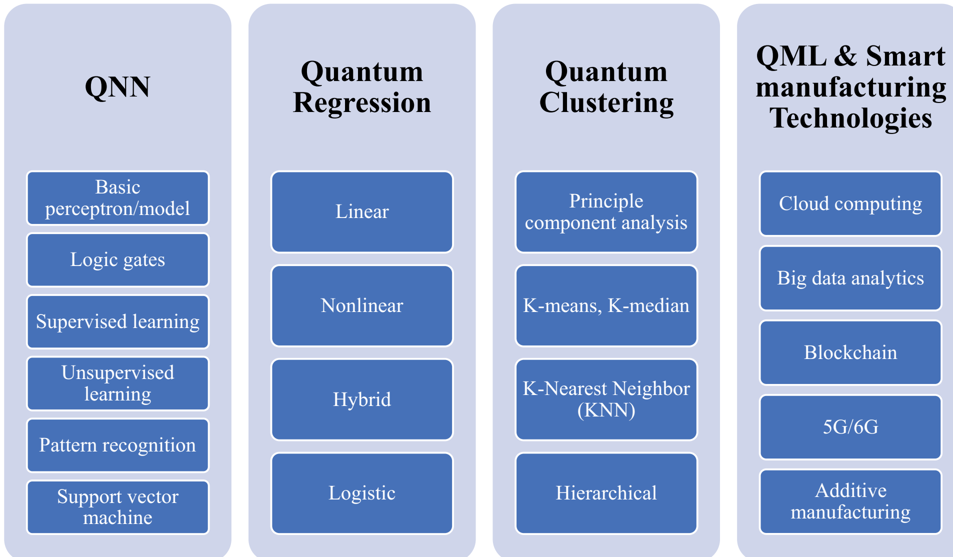

Figure 2. Categorization based on tools and technologies.

Briegel (2018) investigated AI/ML with quantum mechanics and quantum physics. They explored ML applied to quantum physics, ML of QC data, and QC enhancements for ML. Moret-Bonillo (2018) discussed various logic gates for QNN and concluded that Internet speed and connectivity significantly impact new technological implementations in this digital era. Chamola et al. (2021) analyzed QML for 5 G/6 G networks for quantum-based cryptography and highlighted that simulation plays a significant role in understanding new systems. Finally, Coveney and Highfield (2020) deliberated on the use of simulation in the quantum era.

In VP papers, Miller (2019) argued about the integration of QC with AI, ML, and big data. The study emphasized the emergence of human-machine interaction and the significant role of QML in the same. Taylor (2020) put his views on the USA approach for QML. The study shortlisted challenges to be addressed by the USA for the effective adoption of QML. Both these studies argued that QML adoption would shortly be a reality. However, Miller (2019) and Taylor (2020) emphasized security and privacy concerns as a significant challenge for QML.

3.2. *Categories based on tools and technologies*

Further to understand the implementation of QML, the articles were categorized based on tools and technologies. Figure 2 shows the categorization based on tools and technologies. The studies can be broadly classified into four groups, namely i) Quantum neural networks (QNN), ii) Quantum regression, iii) Quantum clustering, and iv) QML and Smart manufacturing technologies. In addition, further subcategories were formed for a detailed understanding of each category.

The basic perceptron is a primary element of neural networks; similarly, the quantum perceptron is a fundamental element of QNN. According to Gao et al. (2018), QC-based algorithms show exponential improvement over classical artificial neural networks (ANN). ANN model and data are replaced by quantum bit-vectors that assist in non-linear mapping (Villmann et al. 2020). Ban et al. (2021) proposed speeding up quantum perceptron using an inverse engineering approach. da Silva et al. (2016a) presented a quantum perceptron over a field-based QNN model, optimizing architecture and weights. Cui et al. (2015) proposed a QNN model with the quantum, hidden, and output layers for time series prediction. Quantized sequential input was given to the quantum layer, the input layer, whereas actual sequential output was produced from the output layer. da Silva et al. (2016b) proposed QNN with weightless architecture and parameters. A learning algorithm was proposed with weightless QNN for measuring performance for various architectures. Ganjefar et al. (2015)

offered QNN and fuzzy wavelet as a design base to enhance power stability. The QNN has four layers: the output layer, product layer, mother wavelet layer, and input layer.

To improve the performance of ANN, Li et al. (2013) employed hybrid QNN with sequence inputs. The simulation and experiment results showed improved generalization and approximation ability of QNN. Tacchino et al. (2020) proposed a QC-based feed-forward ANN model on the same line. Using the Grover learning approach, Liu et al. (2013) modelled feed-forward QNN with one hidden layer. The findings show accurate results for different datasets with various training samples. Finally, Zwolak et al. (2018) implemented the ML approach for the datasets of quantum dots devices obtained through simulation. The study signifies the importance of simulation in QML studies.

In ANN, logic gates help to implement a rule-based system. QC-based logic gates were implemented by Acampora, Schiattarella, and Troiano (2021), Li et al. (2013), and Nguyen et al. (2019). Acampora, Schiattarella, and Troiano (2021) summarized commonly used quantum gates, namely SWAP (for swapping two-qubit states), CSWAP (Conditional SWAP), NOT, CNOT (Controlled-NOT), Rz (for rotating about the Z-axis), S Gate (for 90 degrees rotation about Rz), Ry (for modifying the qubit's magnitude knob), Hadamard H (for equal superpositioning of primary states 0 & 1), and Toffoli CCNOT (Controlled-Controlled-Not). The study proposed Deep Neural Network (DNN) based circuit mapping, and a case study on a five-qubits IBM Q processor showed performance enhancement in mapping accuracy and speed. Li et al. (2013) proposed a controlled Hadamard gate where the model comprises three layers: input, hidden, and output. The output layer had classical neurons, the hidden layer had quantum neurons, and the input layer with input nodes. The simulation results showed that input nodes must be close to sequence length for better results. Nguyen et al. (2019) compared the performance of QNN for pattern classification and logic gates. This benchmarking study has compared various gates such as XNOR, XOR, NOR, OR, NAND, and AND for QNN, CVNN (Complex valued neural net), RVNN (Real valued neural net), and Neural works. The results showed that QNN achieves better results with smaller networks and far fewer epochs.

Supervised learning techniques are popular in ANN, where weights are corrections based on desired responses. Bhatia et al. (2019) used a supervised learning approach to classify the climatic and Iris dataset for QC. The study proposed a quantum classifier based on matrix product states, and simulation analysis showed that the classifier had good learning capability and was efficient for fewer qubits. To address the problem of ample feature space in classification problems, Havlíček et al. (2019) proposed QNN with supervised learning. The experimental results showed better output even in noisy data. Kieferová and Wiebe (2017) offered Golden-Thompson training and relative entropy training for quantum Boltzmann machines, reasonably accurate for complex QC. In the unsupervised learning technique for QNN, Benedetti et al. (2017) used a quantum annealer for training and a combination of qubits and a quantum annealer for testing. The case of image processing was undertaken to test the proposed approach. The results showed that quantum annealer improves the algorithm, which depends on high dimensional sampling and complex probability distribution.

The Hebbian learning rule is one of the basic unsupervised models. Osakabe et al. (2021) proposed Hebbian rule-based QNN, where qubits interaction replaces neuron interaction of traditional ANN. The study suggested Hebbian and anti-Hebbian rules for QC. The results showed improvement in learning performance with a higher probability of target pattern retrieval. Li et al. (2020) and Li et al. (2021) used the pattern recognition approach for QNN implementation. Li et al. (2020) proposed a classifier based on quantum mechanics for feature classification and extraction. The classifier was tested for different kernels such as linear, sigmoid, exponential, polynomial, and Gaussian. The performance parameters measured were specificity, recall, precision, and accuracy. Li et al. (2021) proposed QML for biomedical applications. The steps followed were pre-processing and normalization, dimensionality reduction, classical ML algorithms, and quantum algorithms. The results showed that the proposed algorithm gives better efficacy even with small datasets. Sharma et al. (2021) proposed a quantum-based SVM approach for the health monitoring of additive manufacturing. Features selected were entropy, standard deviation, median, skewness, Root Mean Square (RMS), and kurtosis.

Simulation results were compared for SVM and quantum-based SVM, which showed higher accuracy of the quantum-based system. Date et al. (2021) conducted training on three ML models, namely k-means clustering, SVM, and linear regression, on adiabatic QC computers. The results showed that k-means clustering and SVM perform better in space and time complexities.

Reddy and Bhattacherjee (2021) compared QC-based linear regression, hybrid QNN, quantum Fourier transform-based hybrid QNN, and radial basis function neural network(NN) to predict the atomization of molecular energies. The results show that QC-based linear regression was reasonably accurate compared to the other three methods. Quantum non-linear regression allows a solution through an exhaustive search of the optimization. Panella and Martinelli (2008) proposed a hybrid approach of neural networks and fuzzy logic with non-linear QC for huge search problems. The proposed method offers an optimal solution for the specific search problem. Fujii and Nakajima (2017) proposed a QC reservoir for the rapid processing of information. Experimentation showed that the QC system with five to seven qubits could process the ANN of 500 nodes. Acampora, Schiattarella, and Troiano (2021) proposed logistic regression based on a deep neural network to address circuit mapping in QC. The experimentation on IBM Q processors with five qubits showed consistent accuracy.

Privacy and security concerns are prominent in ML, which are significant barriers to adopting this emerging technology. Wiebe and Kumar (2018) demonstrated QC-based robust principal component analysis (PCA) and used Hamiltonian simulation for testing and validation to address this issue. It was found that QC not only speedups ML system but also improves the security of ML. In similar research on intrusion detection for security, Chen et al. (2020b) proposed a hybrid K-means clustering approach and tested large datasets to show its effectiveness.

Dang et al. (2018) demonstrated a QC-based K-Nearest-Neighbor algorithm for the classification processing of images. The results showed around 80% accuracy with different datasets. Peyton et al. (2020) introduced density tensor representation for QML using clustering and found that the proposed approach was accurate even with few training points per system.

The latest studies that discuss QML and Smart manufacturing technologies are as follows: cloud computing (Akhtar et al. 2020; Liu et al. 2021), Blockchain (Yu et al. 2020; Zhang et al. 2021) Big data analytics (Miller 2019), 5 G/6 G (Akhtar et al. 2020), and Additive manufacturing (Sharma et al. 2021). Liu et al. (2021) proposed a QC conditional generative adversarial network algorithm for human-centric cloud computing.

The algorithm generates discrete and continuous data for qubits. The implementation was done through an open-source QC-based CC platform and showed effective congregate to the Nash equilibrium. In this digital era, big data is essential for ML. Miller (2019) argued that QC processing of big data could be accessible in the future, and thus QML will be the next disruptive technology. On the same line, Akhtar et al. (2020) discussed the significance of QC-based big data and QC-based blockchain as future technologies and highlighted the conceptual framework of ML-based quantum communication. Biamonte et al. (2017) deliberated on linear-algebra-based QML, Quantum-based SVM and Principal component analysis (PCA).

Three case studies were discussed by Ban et al. (2021), Li et al. (2021), and Gonçalves (2018). Ban et al. (2021) implemented an inverse engineering-based sigmoidal response to address the unitary and linear QC framework. The results showed the performance improvement of the perceptron. Li et al. (2021) used QML-based classification of cancer of different types such as colorectal, liver, lung, kidney, breast, and brain. The study classified ten models for determining performance in terms of score and accuracy. Finally, a case study on robotics using QNN was proposed by Gonçalves (2018), which was implemented on IBM's five qubits using cloud computing.

3.3. *Descriptive analysis*

This part of the paper gives a detailed classification of shortlisted articles year-wise, country-wise, and journal-wise. Figure 3 shows the number of articles published year-wise.

As shown in Figure 3, the number of papers published in QML was considerable from 2015. From 1995 to 2012, there were two research articles in this domain. In comparison, most papers (10 of them)

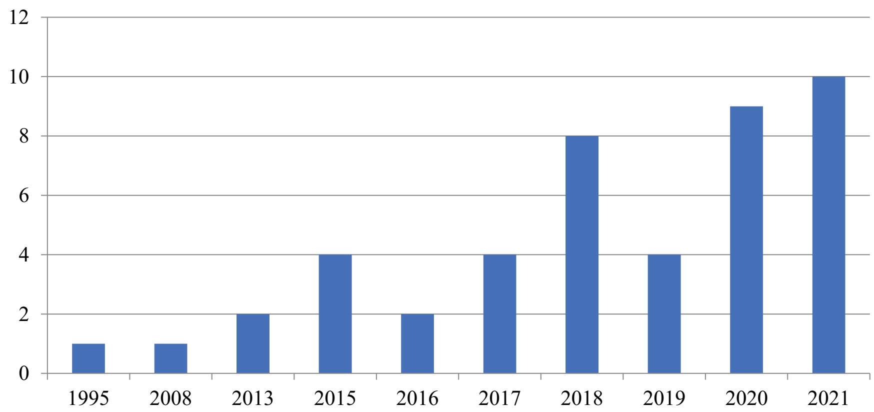

Figure 3. Year-wise number of papers in QML.

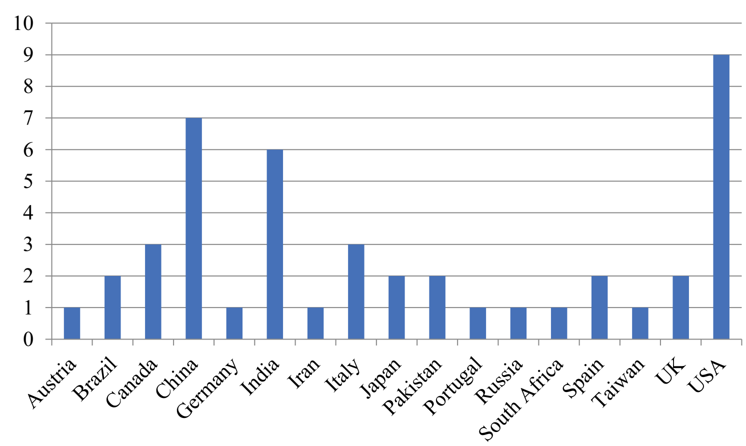

Figure 4. Country wise number of papers in QML.

were published in 2021. Figure 4 shows the country-wise distribution of documents in QML.

As shown in Figure 4, most articles (9 of them) were published in the USA, whereas seven articles were from China. India was third on the list with six articles. The geographical analysis of the articles is shown in Table 3, in which the distribution of papers across the five continents is indicated. It may be inferred from Table 3 that most articles (19, 42.23%) belong to Asia, followed by North and South America (14, 31.11%). In contrast, the contribution of Australia is minimum (1, 2.22%).

As shown in Table 3, countries worldwide have already started research and implementation work on QML. China and the USA have carried out significant work. However, Regetti, Xanadu, Honeywell, D-Wave Solutions, QC Ware, Zapata Computing, 1QBit, and ColdQuantahave begun to invest in QML (Bova, Goldfarb, and Melko 2021; de Lima Marquezino, Portugal, and Lavor 2019). Table 4 shows the journal-wise number of papers in QML.

Table 3. Geographical distribution of papers.

Geographical area	Number of articles	Percentage (%)
Asia	19	42.23
North and South America	14	31.11
Europe	10	22.22
Africa	1	2.22
Australia	1	2.22
Total	**45**	**100**

As shown in Table 4, Neural Networks (NN) had the highest number of four articles, and Physical Review (PR) had three articles on QML. Six journals, namely Nature (NATU), Neural Computing and Applications (NCA), Neurocomputing (NC), PloS One (PLO), Progress in Artificial Intelligence (PAI), and Scientific Reports (SR), had two publications each. The remaining 26 journals had only one publication each. The

Table 4. Journal-wise distribution of papers.

S. N.	Journal	Abbreviation	Number of papers
1	Advances in imaging and electron physics	AIEP	1
2	Computer Communications	CCom	1
3	Contemporary Physics	CPhy	1
4	EURASIP Journal on Wireless Communications and Networking	EURASIP	1
5	Human-centric Computing and Information Sciences	HCIS	1
6	IEEE Transactions on Emerging Topics in Computing	IEEEC	1
7	IEEE Transactions on Fuzzy Systems	IEEEF	1
8	IEEE Transactions on Neural Networks and Learning Systems	IEEEN	1
9	IEICE Transactions on Information and Systems	IEICE	1
10	IET Collaborative Intelligent Manufacturing	IETC	1
11	Journal of Big Data	JBD	1
12	Journal of Computational Science	JCS	1
13	Knowledge-Based Systems	KBS	1
14	Machine Learning: Science and Technology	MLST	1
15	Nature	NATU	2
16	Neural Computation	NC	1
17	Neural Computing and Applications	NCA	2
18	Neural Networks	NN	4
19	Neural Networks and the Quantum Force Interpretation	NNQFI	1
20	Neurocomputing	NCOM	2
21	New Journal of Physics	NJP	1
22	Patterns	PAT	1
23	Physical Review	PR	3
24	PloS one	PLO	2
25	Progress in Artificial Intelligence	PAI	2
26	Quantum Information Processing	QIP	1
27	Quantum Science and Technology	QST	1
28	Quantum	QUA	1
29	Reports on Progress in Physics	RPP	1
30	Science & Technology Libraries	STL	1
31	Science Advances	SA	1
32	Scientific Reports	SR	2
33	Telecommunications Policy	TP	1
34	The Journal of Physical Chemistry A	JPCA	1
Total			**45**

Table 5. Year-wise distribution of articles according to country.

Year	1995	2008	2013	2015	2016	2017	2018	2019	2020	2021	Total
Country											
Austria							1				**1**
Brazil					2						**2**
Canada						2	1				**3**
China			1	1			2		2	1	**7**
Germany									1		**1**
India								1	1	4	**6**
Iran				1							**1**
Italy		1							1	1	**3**
Japan						1				1	**2**
Pakistan									1	1	**2**
Portugal							1				**1**
Russia							1				**1**
South Africa				1							**1**
Spain				1			1				**2**
Taiwan			1								**1**
UK								1	1		**2**
USA	1					1	1	2	2	2	**9**
Total	**1**	**1**	**2**	**4**	**2**	**4**	**8**	**4**	**9**	**9**	**45**

Table 6. Year-wise distribution of articles according to journal.

Year	1995	2008	2013	2015	2016	2017	2018	2019	2020	2021	Total
Journal											
AIEP	1										**1**
CCom										1	**1**
CPhy				1							**1**
EURASIP										1	**1**
HCIS									1		**1**
IEEEC									1		**1**
IEEEF		1									**1**
IEEEN								1			**1**
IEICE										1	**1**
IETC										1	**1**
JBD								1			**1**
JCS									1		**1**
KBS									1		**1**
MLST										1	**1**
NATU						1		1			**2**
NC								1			**1**
NCA									1	1	**2**
NN			1	2	1						**4**
NNQFI							1				**1**
NCOM			1		1						**2**
NJP							1				**1**
PAT										1	**1**
PR						3					**3**
PLO							2				**2**
PAI				1			1				**2**
QIP							1				**1**
QST									1		**1**
QUA										1	**1**
RPP							1				**1**
STL									1		**1**
SA							1				**1**
SR										2	**2**
TP									1		**1**
JPCA									1		**1**
Total	**1**	**1**	**2**	**4**	**2**	**4**	**8**	**4**	**9**	**10**	**45**

year-wise distribution of articles according to country and journal is given in Tables 5 and 6, respectively. These tables indicate that research articles have considerably increased in the last two years.

4. Findings and discussion

This part of the paper addresses the second research objective (RO2) – 'To investigate the state of the art of QML and smart manufacturing'. Further, QML integrated smart manufacturing framework is proposed (RO3).

Figure 5 shows the categories based on the type of paper. It shows that the case implementation of QML is minimal. However, the commissions were at the prototype level, and the adoption of QML will be a reality soon. Figure 6 shows categories of the paper-based on technique/technology. It indicates that the majority of the studies discussed QNN. To understand types based on technique/technology, further sub-categories were formed. Table 7 shows sub-categories discussed by 45 research papers shortlisted for the study. Thirty-three papers out of 45 discussed only one technique/technology. Six articles discussed two techniques/technologies, whereas five articles discussed three techniques/technologies. Only one study examined five techniques/technologies. It shows that researchers are focusing on one/two techniques/technologies for QML.

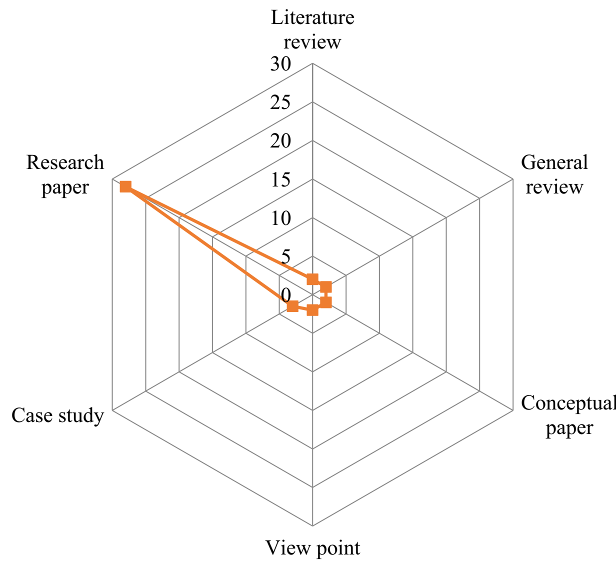

Figure 5. Categories based on type of paperCategories based on type of paper.

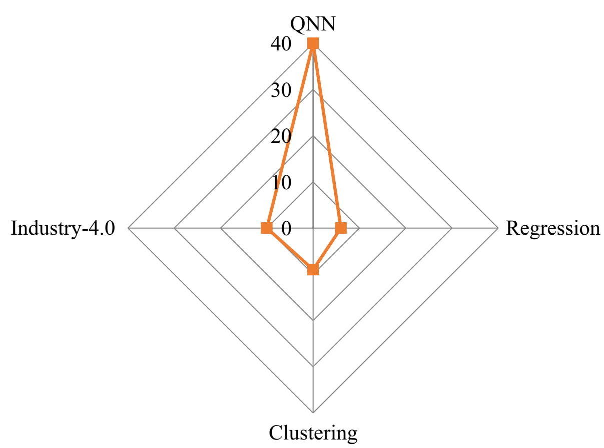

Figure 6. Categories based on technique/technology.

As shown in Table 7, QNN is the most popular among the researchers. Figure 7 shows sub-categories of QNN. Basic perceptron/model is the first step of QNN and was discussed by most studies. It was followed by SVM, supervised learning, logic gates, unsupervised learning, and pattern recognition.

QC can be implemented for supervised and unsupervised learning. QC efficiently calculates classical distances for K- means clustering, K- nearest neighbour, and SVM methods. Regression methods and Smart manufacturing technologies are gaining attention in QML studies as they enable fast information processing. However, these implementations were at the simulation or prototype level. The real-time performance will help to understand the issues of QML for case applications. Thus, to adopt QML, it is necessary to identify the following critical research directions.

(i) *Open-Source Software* – Quantum algorithms were designed and tested on propriety software from either in-house or commercial vendors. However, there is a need for open-source software for the QML domain. This will ensure reproducibility, knowledge sharing, broader publicity, QC community building, and cost-effectiveness.

(ii) *Benchmarking issue* – It is challenging to decide which QML algorithm is better than

Table 7. Categories and sub-categories of technique/technology.

S. N.	Publication	Quantum neural network						Quantum regression				Quantum clustering				QML & Smart manufacturing technologies					Total
		BP/M	LG	SL	USL	PR	SVM	LR	NLR	HR	LoR	PCA	KM	KNN	Hi	CC	BCT	5G/6G	BDA	AM	
	Acampora1 and Schiattarella (2021)		√				√				√										**3**
	Akhtar et al. (2020)															√	√	√			**3**
	Ban et al. (2021)	√																			**1**
	Benedetti et al. (2017)				√																**1**
	Bhatia et al. (2019)			√																	**1**
	Biamonte et al. (2017)						√					√									**2**
	Chamola et al. (2021)																	√			**1**
	Chen et al. (2020b)												√								**1**
	Coveney and Highfield (2020)																		√		**1**
	Cui et al. (2015)	√																			**1**
	da Silva et al. (2016a)	√																			**1**
	da Silva et al. (2016b)	√																			**1**
	Dang et al. (2018)													√							**1**
	Date et al. (2021)						√	√					√								**3**
	Deshmukh and Mulay (2021)														√						**1**
	Dunjko and Briegel (2018)			√	√		√														**3**
	Fingerhuth et al. (2018)	√																			**1**
	Fujii and Nakajima (2017)								√												**1**
	Ganjefar et al. (2015)	√																			**1**
	Gao et al., (2018)	√																			**1**
	Gonçalves (2018)	√																			**1**
	Havlíček et al. (2019)			√																	**1**
	Kak (1995)	√																			**1**
	Kieferová, andWiebe (2017)			√																	**1**
	Li et al. (2013)	√	√																		**2**
	Li et al. (2020)			√		√															**2**
	Li et al. (2021)					√															**1**
	Liu et al. (2013)	√																			**1**
	Liu et al. (2021)															√					**1**
	Miller (2019)																		√		**1**
	Moret-Bonillo (2015)	√																			**1**
	Moret-Bonillo (2018)		√																		**1**
	Nguyen et al. (2019)	√	√																		**2**
	Osakabe et al. (2021)				√																**1**
	Pande and Mulay (2020)	√																			**1**
	Panella and Martinelli (2008)								√												**1**
	Peyton et al. (2020)														√						**1**
	Reddy and Bhattacherjee(2021)							√		√											**2**

(*Continued*)

Table 7. (Continued).

		Quantum neural network						Quantum regression				Quantum clustering				QML & Smart manufacturing technologies					
S. N.	Publication	BP/M	LG	SL	USL	PR	SVM	LR	NLR	HR	LoR	PCA	KM	KNN	Hi	CC	BCT	5G/6G	BDA	AM	Total
	Schuld et al. (2015)			√	√		√						√	√							**5**
	Sharma et al. (2021)						√													√	**2**
	Tacchino et al. (2020)	√																			**1**
	Taylor (2020)	√														√			√		**3**
	Villmann et al. (2020)	√																			**1**
	Wiebe and Kumar (2018)											√									**1**
	Zwolak et al. (2018)	√																			**1**
Total		**18**	**4**	**6**	**4**	**2**	**6**	**2**	**2**	**1**	**1**	**2**	**3**	**2**	**2**	**3**	**1**	**2**	**3**	**1**	**65**
Category wise total		**40**						**6**				**9**				**10**					

Note- BP/M: Basic perceptron/model, LG: Logic Gates,SL: Supervised learning, USL: Unsupervised learning, PR: Pattern recognition, SVM: Support vector machine, LR: Linear regression, NLR: Non-linear regression, HR, Hybrid regression LoR: Logistic regression, PCA: Principal component analysis, KM: K-means, K-median: KNN: K- Nearest-Neighbor, Hi: Hierarchical, CC: Cloud computing, BCT: Blockchain, BDA: Big data analytics, AM: Additive manufacturing.

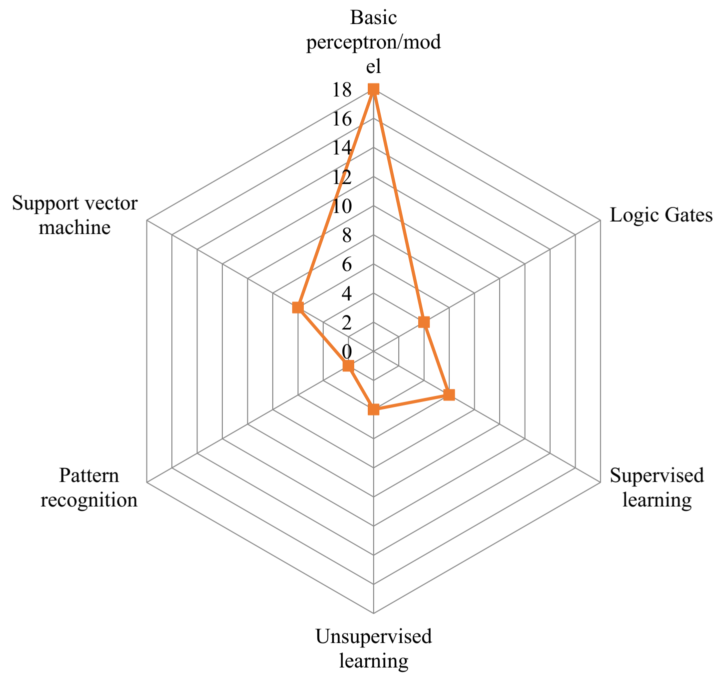

Figure 7. Sub-categories of QNN.

the other. Algorithm complexity is one standard parameter used for comparing the algorithm's efficiency. However, it could not be applicable in all cases. Therefore, proper benchmarking, particularly with the latest heuristic method, needs to be addressed.

(iii) *Quantum cybernetics* – Communication between machines and humans, plays a vital role in implementing new technology. Autonomous QC will ensure real-time implementation for industrial applications. However, concerns about data privacy and security must be addressed. Also, the human-machine interface must be designed for ease of use.

(iv) *Input and output problem* – Even though QML provides speedy data processing, the cost of input data reading dominates the cost of the QML algorithm. Therefore, the output produced by QML needs to be understood. However, the statistics summary for the solution is at the initial stage of its development. Thus more research is needed about input and output data issues in QML.

(v) *Cost issues* – Being a new technology, cost calculation is a challenge, particularly for large problems. Moreover, there is often less knowledge about the actual number of parameters for QML. Also, cost calculation for prototype and real systems differs. Thus, calculating the actual cost and return on investment is a challenge for QML implementation.

(vi) *Hardware issues* – QC systems are in their early days of implementation. Thus hardware implementation of the system is a big challenge as it requires various layers of abstraction. Four broad paradigms of QC are adiabatic QC, continuous variable gate model QC, discrete variable gate model QC, and quantum simulators. It is challenging to decide on the level of abstraction in these paradigms, which makes hardware implementation difficult.

(vii) *Integration with Smart Manufacturing Technologies* – Potential technologies such as big data analytics, the Internet of Things (Yang et al. 2019), cloud computing, blockchain, 6 G, etc., will be assisting QC implementation. However, the research challenges of integrating these technologies with QML need to be addressed.

The above research directions must be explored for the effective adoption of QML. Also, factors for the

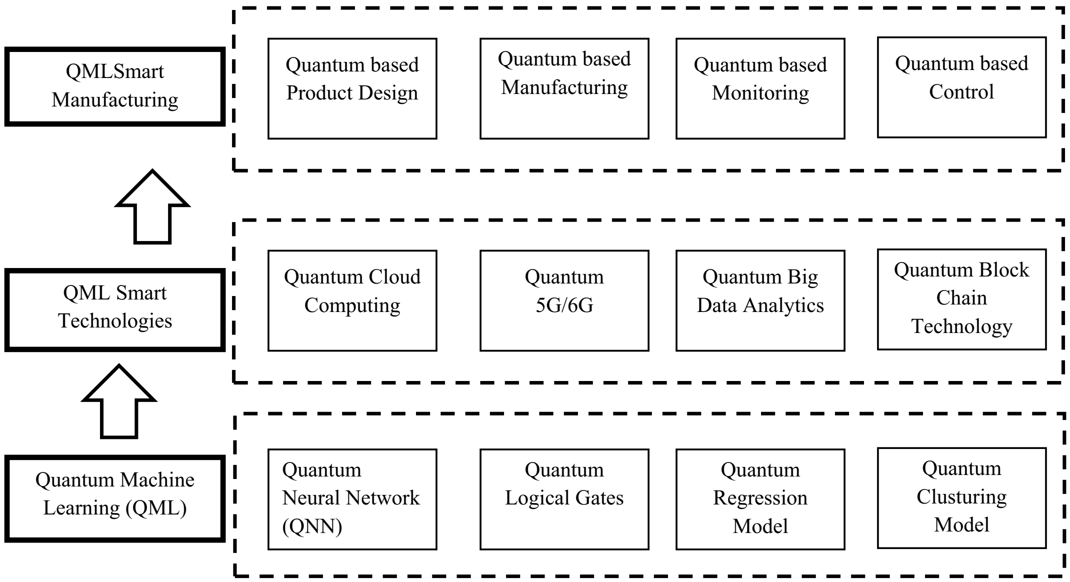

Figure 8. Framework of QML integrated for smart manufacturing.

adoption of QML can be found based on the themes and research directions given in the study. Based on the study's findings, Figure 8 presents the Framework of QML-integrated smart manufacturing.

As shown in Figure 8, a quantum perceptron/model must be developed first, followed by logic gates to incorporate essential mathematical functions. Then, further supervised or unsupervised QNN, QNN-based pattern recognition, and SVM methods can be used. ANN forms the base for ML; on the same line, QNN forms the base for QML. Thus, QNN models must be implemented as a starting step for QML. Then, further quantum regression models based on linear, non-linear, hybrid, and logistic regression can be used. Also, PCA, KNN, K-means, and hierarchical methods of QNN-based clustering can solve real-life problems. Advancements in Smart manufacturing technologies have brought a sea change in the manufacturing and supply chain (Anzoom, Nagi, and Vogiatzis 2021) and digital twins (Gaikwad et al. 2020). QML can assist this Smart manufacturing revolution by processing big data in less time. Thus QML based cloud computing, BDA, 5 G/6 G, etc., would be a reality in the future.

5. Conclusion

This study delivers a systematic literature review of QML to foster better clarity about this upcoming area. To the best of the authors' knowledge, this is the first SLR on QML. The methodology adopted for the study had three phases, namely planning, execution, and detailed research and outcome. In the first planning phase, inputs from the expert panel were taken. In the second conduction phase, keywords were selected from the Scopus database, and 45 peer-reviewed journal articles were selected for a detailed study. In the final stage, these articles were studied in detail to comprehend the state of the art of QML. The considered period for the selected 45 research articles was 1995 to 2021. The main objective of conducting this SLR was to identify themes and categories of QML. Based on these findings, research perceptive and future directions of QML were identified. Furthermore, categories of papers were discussed based on the type of articles and techniques discussed in the articles.

Moreover, descriptive analysis was carried out to classify articles year-wise, country-wise, region-wise, and journal-wise. Based on tools and technologies, four broad categories of paper were identified: quantum neural network (QNN), quantum regression, quantum clustering, and QML & Smart manufacturing technologies. To understand these categories in detail, further sub-categories were formed. The detailed analysis shows that the implementation of QML is at an initial stage. Simulation and prototypes were mainly discussed in the articles. Very few actual case implementations were discussed. However, it must be noted that the number of published articles in the last two years has increased in all regions. This shows awareness about QML is substantially growing owing to its advantages.

5.1. Theoretical implications

This study analyses literature articles for understanding the state of the art of QML. The paper contributes to existing theory through an exhaustive literature survey and detailed analysis. Analytical presentation of findings of the study can be used by the researchers in the field of QC and ML for in-depth analysis of the topic. Categories and sub-categories formed will help academicians to understand this new domain in a better way. Furthermore, the descriptive analysis will help to understand the country-wise trends in the QML area. Further, academicians and researchers can use identified research directions for their future work.

5.2. Practical implications

This paper is helpful to practitioners, top management, and policymakers. The summarized analysis picture can be beneficial to practitioners to understand QML themes. Identified research directions can be utilized to decide on a further course of action for the implementation. Organizations from developed countries such as the USA, China, etc., have already started QML implementation, and emerging economies need to follow up to remain competitive in the global markets. An organization's top management can get a roadmap for the effective implementation of QML and must understand the benefits. Policymakers can utilize the study's findings to decide how they can assist organizations in implementing QML. Finally, top management and policymakers must understand that QML will be the next disruptive technology.

5.3. Limitations of the study

Although this study is exhaustive, it has a few limitations. First, the data were collected from the Scopus database; however, other databases such as Web of Science were not taken into account for this study. Second, this study considered peer-reviewed English-language articles from reputed journals. However, the thesis, textbooks, conference proceedings, and book chapters were not considered. Third, in this study, QC for evolutionary algorithms, genetic algorithms and optimization were not explored as they would be studied in detail in future literature survey articles. Fourth, this study does not consider reinforcement learning and generative adversarial networks. Finally, this study centred on QML allied domains and would be helpful for researchers and practitioners in this new area.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

The authors confirm that the data supporting the findings of this study are available within the article [and/or] its supplementary materials.

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