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Article

An Artificial Intelligence (AI) Framework To Predict Operational Excellence: UAE Case Study

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Abstract: The integration of artificial intelligence (AI) into the European Foundation for Quality Management (EFQM) business excellence model is a promising approach to improve the efficiency and effectiveness of excellence in organizations. This research paper's integrated framework follows the ISO/IEC 23053 standard in addressing some of the concerns related to time and cost associated with the EFQM model, achieving higher EFQM scores, hence operational excellence. A case study involving a UAE government organization serves as a sample to train the AI framework. Historical EFQM results from different years are used as training data. The AI framework utilizes the unsupervised machine learning technique known as k-means clustering (with k=2). This technique follows the ISO/IEC 23053 standard to predict EFQM output total scores based on criteria and sub-criteria inputs. The research paper's main output is a novel AI framework that can predict EFQM scores for organizations at an early stage. If the predicted EFQM score is not high enough, then the AI framework provides feedback to decision makers regarding the criteria that need reconsideration. Continuous use of this integrated framework helps organizations attain operational excellence. This framework is considered valuable for decision makers as it provides early predictions of EFQM total scores and identifies areas that require improvement before officially applying for the EFQM excellence award. This approach can be considered as an innovative contribution and enhancement to knowledge body and organizational practices.

Keywords: operational excellence; EFQM; artificial intelligence; ISO/IEC 23053 standard

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1. Introduction

1.1. Theoretical Background

Organizations primarily focused on quality and Total Quality Management (TQM) measures to improve their operations before the emergence of business excellence models like the Malcolm Baldrige and the European Foundation for Quality Management (EFQM). These approaches were foundational in promoting a culture of continuous improvement and customer satisfaction. However, business excellence has become a prominent topic in the past few decades, and various models and frameworks have been developed to assess and enhance organizational performance beyond just quality [1].

Figure 1 shows the evolution of quality management concept. Quality inspection (Quality 1.0, 1900s) represented the early days of quality management and inspected finished products to identify defects. Quality was associated with the physical properties of products [2]. The quality control (Quality 1.0, 1920s) emphasized product inspection. During the production process, it introduced more systematic methods for defect identification and correction [2]. Later, quality assurance (Quality 2.0, 1950s) included both product and process quality. This stage witnessed the emergence of ISO standards, which provided guidelines for ensuring consistent quality in manufacturing and other industries. In 1980s, Total Quality Management (TQM, Quality 3.0, 1980s) included not only product and process quality but also the entire organization's culture and operations. It focused on customer satisfaction, continuous improvement, and employee involvement. During this era, various ISO standards were developed, and business excellence models like EFQM gained prominence [2]. In 2017, Quality 4.0 (2017) represents the latest stage in the evolution of quality management, accompanying the fourth industrial revolution (Industry 4.0). It extends the principles of TQM to include not only product, process, and company aspects but also integrates customer and supplier needs. Quality 4.0 leverages technologies such as artificial intelligence (AI) and machine learning (ML) to improve quality management practices.

This research paper introduces a novel integrated AI framework following ISO/IEC 23053 standard to predict EFQM scores, hence enhancing operational excellence. This research has great implications on organizations aiming to improve their processes and overall performance.

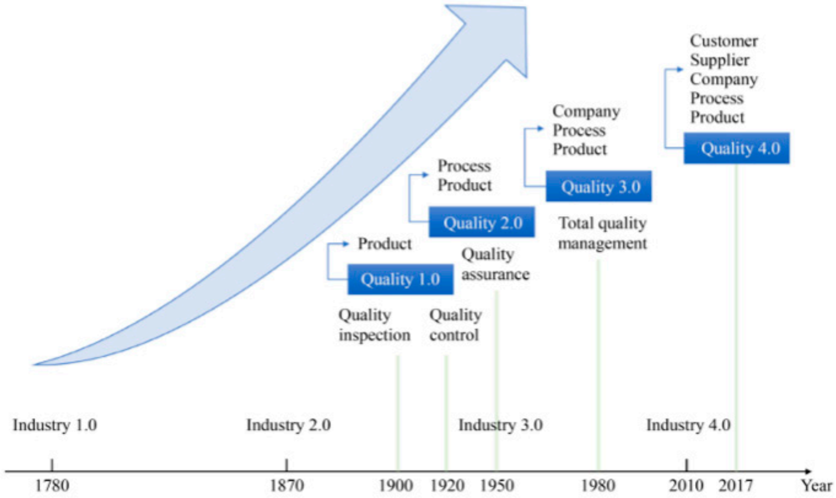

Figure 1. Evolution of Quality [2].

2. Materials and Methods

2.1. Concepts Overview

The European Foundation for Quality Management (EFQM) has played a vital role in the field of business excellence and quality management. EFQM was established in 1992 in European countries as a business excellence model. It was initially created to enhance and assess quality management practices in organizations. Over the years, EFQM was updated and revised in 1999 and 2003[3]. These updates likely reflected the evolving understanding of quality management principles and practices.

EFQM continued changing to adapt different business environments and management paradigms. It underwent crucial modifications in 2010 and 2013 [5]. EFQM's influence extended far beyond Europe to be recognized and adopted not only within Europe but also in other regions of the world, including the Middle East, Asia, South America, and South Africa. This global reach is evidence to the model's adaptability and applicability in diverse cultural and industry contexts.

EFQM's versatility is evident in its application across various industries, including education [4] information technology [6], healthcare [7], and more. This adaptability reflects its effectiveness as a business excellence model with wide applicability. Applying the EFQM model has positive effect on the sustainability of stakeholders within organizations [7]. This come along with the broader objective of business excellence models, which aim to drive overall organizational improvement and long-term success.

EFQM is adopted by numerous global organizations as a business model success and this goes back to its success and rapid evolution. Furthermore, it is recognized as a valuable framework for achieving excellence and continuous improvement.

EFQM has evolved over the years to stay relevant and effective in supporting organizations in their excellence journey. Its global acceptance and application across a wide range of industries

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represent its enduring value in the field of quality management and business excellence [9].EFQM model experienced massive evolution which is summarized in the following figure.

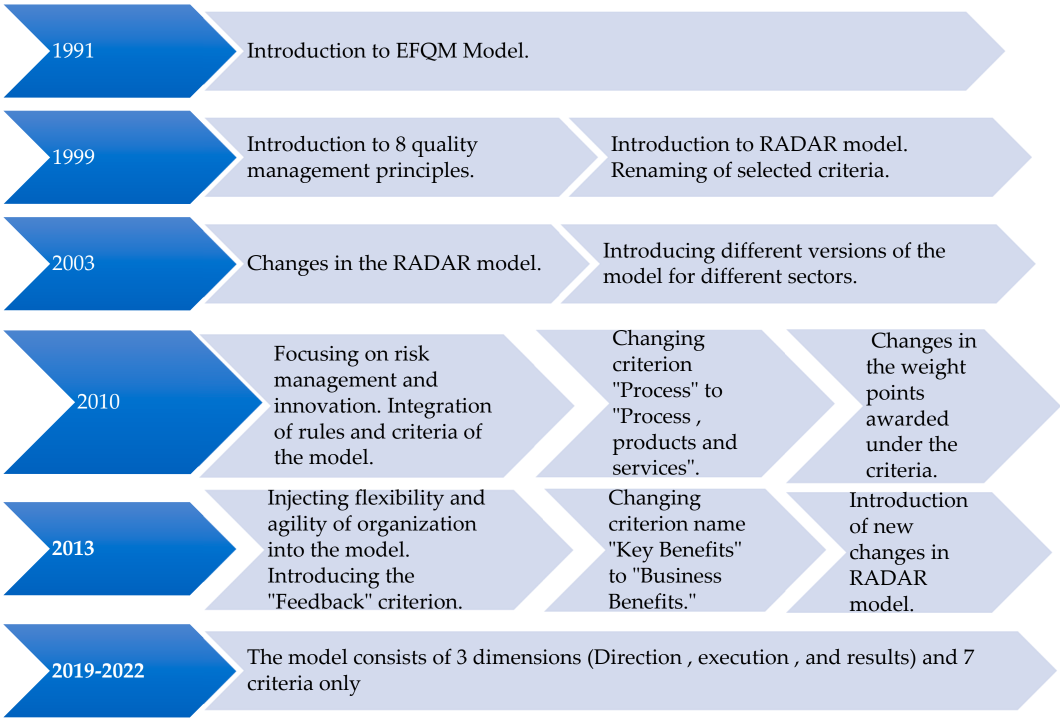

Figure 2. EFQM evolution summary.

The EFQM model appears to have incorporated additional criteria and elements to better address contemporary challenges and organizational needs as shown in Figure 3. The criteria in this modified EFQM model in 2013 include leadership, people, strategy, partnership and resources, processes, people results, customer results, society results, and key results

Learning, creativity, and innovation are added to the EFQM model. It highlights the importance of continuous learning, creativity, and innovation in achieving excellence and competitiveness in today's dynamic business environment. The inclusion of "Learning, Creativity, and Innovation" shows the recognition that organizations must adapt and innovate to stay competitive and address evolving customer and market demands. This modification goes along with the broader trends in business management, focusing on the need for organizations to be agile and forward thinking.

This modified EFQM model provides a more comprehensive framework for assessing and enhancing organizational excellence, considering a wider range of factors that contribute to sustained success and innovation.

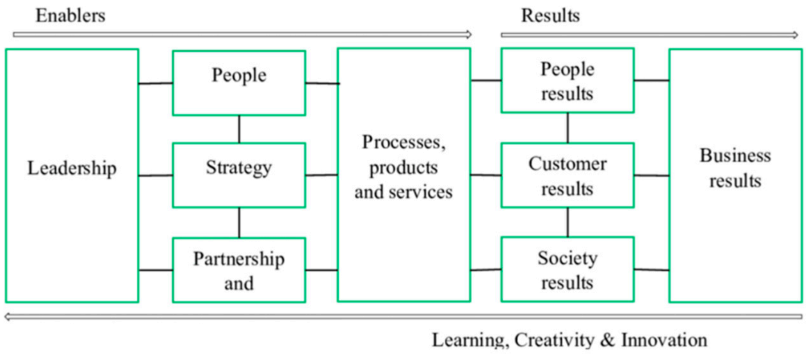

Figure 3. EFQM Framework 2013 [11].

European Foundation for Quality Management (EFQM) is a business excellence model where the organizations applying it meet the sustainability of the stakeholders [8]. It can be used in different sectors like education [4] and information technology [6] health care [7], construction [27].

- EFQM framework is made up of the following main principles as described in [28];
- Result orientation;
- Customer orientation;
- Leadership and consistency of objectives;
- Management by processes and facts;
- Development and involvement of people;
- Development of partnerships;
- Social responsibility of the organizations.

To implement these principles, we need three phases: Initiation, realization and maturity [27]. EFQM is divided into 2 categories, which are enablers and results. Enablers' criteria are responsible for key activities management. The results criteria are responsible for the way the results of an organization are achieved. The criteria include leadership, strategy, people, alliances, resources, processes, products and services [7]. EFQM can be also applied to many domains like the education [4], banking, hotels, public sectors [9], and construction like the case done in Turkey [27].

Most EFQM papers referred to in this paper were held in Spain, published in 2015 and 2023 and mostly applied in the healthcare and education sectors as shown in figure 4.

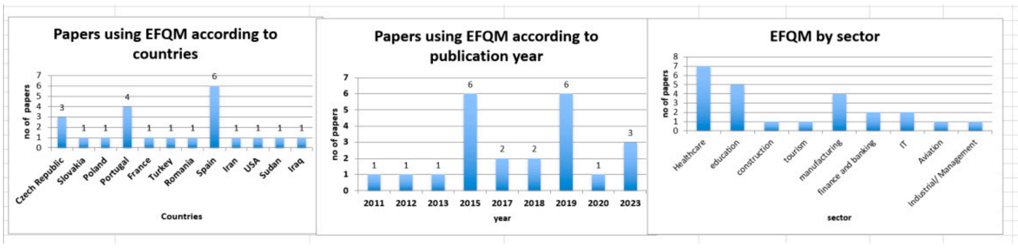

Figure 4. EFQM papers classified by countries, publication year, and sector.

Artificial Intelligence (AI) is a field of computer science and technology that emphasizes on creating systems and machines that can perform jobs requiring human intelligence. These tasks include reasoning, problem-solving, learning, perception, language understanding, and decision-making [8]. AI research began in the 1950s with the target of creating machines that can mimic human intelligence. Early AI systems were rule-based and relied on explicit programming to simulate human reasoning. However, these systems did not work well in complex real-world problems. Therefore, machine learning- a subset of AI- emerged in the 1970s. It introduced a paradigm shift by emphasizing on the ability of machines to learn from data and enhance their performance without being explicitly programmed.

Machine learning's fundamental concept is to allow computers to learn and adapt from data. This is achieved through various algorithms that can specify patterns, make predictions, and make decisions relative to the data they are provided [12]. Machine learning allows machines to develop their own programs based on previously learned examples. This is achieved through training on large datasets, where the machine learns the underlying patterns and relationships in the data [8]. Machine learning is widely applied in terrorism prediction [10], cancer prediction [13], and sports result prediction [14]. These applications leverage the ability of machine learning algorithms to find hidden patterns and correlations in data. Machine learning techniques are classified into categories: supervised learning, unsupervised learning, semi-supervised learning, reinforcement learning, and deep learning as shown in Figure 5 [12].

Machine learning continues to advance rapidly and has become a basic tool in various fields, including healthcare, finance, natural language processing, computer vision, and autonomous systems. Its potential to extract valuable patterns from data makes it a powerful technology with a wide range of applications.

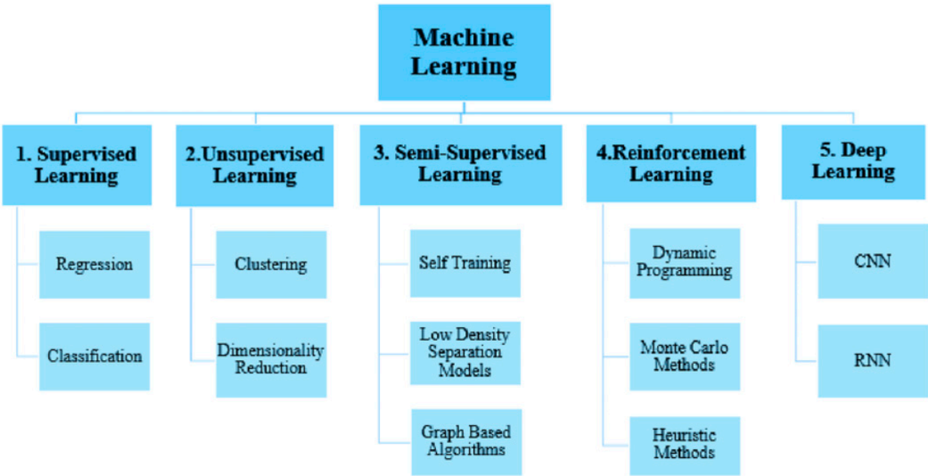

Figure 5. Machine learning algorithms [12].

Recently machine learning has spread over many applications and industries. It can be found in web search, siris, pricing prediction, transportation, crime prediction, and healthcare [30]. Unfortunately, few papers talked about using AI in predicting EFQM scores. Therefore, this paper comes out with a framework combining AI techniques into the EFQM model. In this framework, k-means unsupervised machine learning technique is adopted.

Unsupervised leaning works on finding common input points in the data as the previously trained. Clustering of inputs is a good description of this process where the inputs are correlated based on their statistical properties.

Unsupervised data learning method do not need any labeled output to train the algorithm. It is more subjective since human will not interfere as in supervised learning [32]. The main objective of unsupervised learning is to learn more about data by identifying patterns found in the data itself. In other words, it learns by itself an input pattern and compares it with the following input patterns.

The K-means clustering is a simple and powerful unsupervised machine learning technique that works with most industries [33]. It groups similar inputs together to form meaningful clusters. Therefore, clustering is the process of dividing data into groups or clusters sharing the same characteristics and minimizing data distances within the same cluster [33].

In this research paper, K-means clustering (k=2) which is an unsupervised machine learning technique is applied and accuracy score values are calculated.

Literature review shows the injection of AI into different fields and Table 1 represents some of these papers.

Table 1. Summary Literature Review of AI into Different Industries.

Name of paper	Country/Year	Author/ Publisher	General Description	Applied Area/Field	Strengths of applied technique/ Method	Challenges/ Limitation
1-The Impacts of Robotics, Artificial Intelligence on Business and Economics [17].	Turkey, 2015	(Dirican C., 2015), Elsevier	Injecting AI concepts into economical concepts	Economics	Enhance different economical perspectives.	Increased unemployment
2- Decision Making System using Machine Learning and Pearson for Heart Attack [41].	India, 2017	(Thirumalai C., et al., 2017), IEEE	Using machine learning to predict heart attacks of patients. SPSS used for data validation	Healthcare	Get predicted medical results from scanning directly on phone application, so helps in decision making	N/A

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3- Intelligent human resource information system (i-HRIS): A holistic decision support framework for HR excellence [18].	Malaysia, 2018	(Masum M., et al., 2018), Researchgate	Integrating intelligent HR with intelligent decision making with knowledge discovery database	Human Resources, Artificial intelligence.	Improve structured, semi-structured, and unstructured HR decision making process.	Data can be used to predict suitable AI techniques to be used. The model can be broader by using wireless protocols.
4- Artificial intelligence and the future of global health [15].	USA, 2020	(Schwalbe N., and Wah B., 2020), Elsevier	AI into global health categories	Healthcare	Accelerate sustainability. Improved health outcomes	No ethical considerations
5-Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities [19].	South Africa, 2020	(Bag S., et al, 2020), Elsevier	Description of reasons why firms use AI into manufacturing.	Manufacturing	Enhance sustainable manufacturing and develop circular economy.	Low skill level
6-A strategic framework for artificial intelligence in marketing [24].	Taiwan, USA, 2020	(Huang M., and Rust R., 2020), Springer	Injecting AI techniques into strategic marketing planning	Marketing	Enhance strategic marketing process	Biased, less human intervention
7- Artificial Intelligence Forecasting Census and Supporting Early Decisions [20].	USA, 2020	(Griner T., et al., 2020), Wolters Kluwer Health	Alex is an AI technique that helps nurses for occupancy prediction and decision making.	Healthcare, Nursing.	Enhance operational excellence, and safety	N/A
8-Manufacturing service innovation platform based on 5 G network and machine learning [16]	China, 2020	(Gao N., et al., 2020), Elsevier	Using AI to organize innovation and achieve organizational excellence	Manufacturing, services.	Enhance customer satisfaction, service innovation, and organizational performance.	N/A
9- Artificial Intelligence (AI) and Its Applications in Indian Manufacturing: A Review [21]	India, 2021	(Rizvi A., et al., 2021), Springer	AI integrated into manufacturing firms in India	Manufacturing	Improve quality and reduce errors	High installation cost and maintenance.
10- Predicting the COVID-19 infection with fourteen clinical features using machine learning classification algorithms [22].	China, 2021	(Arpaci I., Huang S., Al-Emran M., Al-Kabi M, 2021), Springer	AI model is used to predict COVID 19 from 14 criteria with limited testing resources	Medicine, Healthcare	Predict COVID 19 cases ahead of time when RT-PCT kids are limited.	Low sample size. Unavailable data about COVID 19 symptoms in predicting the infection.
11- Applications of Explainable Artificial	China, UK,2022	(Zhang, Y.;Weng, Y.; Lund,	Apply AI in surgeries	Medicine, Healthcare	Usage of AI in surgeries	N/A

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Intelligence in Diagnosis and Surgery [23].	J.,2022), Diagnostics				
12-Impact of Artificial Intelligence on Dental Education: A Review and Guide for Curriculum Update [35].	(Thurzo, A.; Strunga, M.; Urban, R.; Surovková, J.; Afrashtehfar, K.I., 2023), Education Sciences	Usage of AI in dentistry	Medicine , Dentistry	Usage of AI in new fields in medicine.	N/A

Integrating AI following ISO/IEC 23053 into business excellence models represents a crucial need in academia and the marketplace. This integrated framework has the potential to drive efficiency, cost savings, innovation, and competitive benefits for organizations, making it a valuable area of study and application.

After applying AI in many industries like medicine to predict breast cancer [23], and in dental education [35], and its massive use during the Covid 19 pandemic, appeared the crucial need for AI to be ISO certified. Therefore, ISO/IEC 23053 standard for AI has emerged to fulfill the necessity of standardization and to regulate and certify AI techniques.

The International Organization for Standardization (ISO), an independent, nongovernmental international organization, has begun to develop standards around AI along with the International Electrotechnical Commission (IEC) through Subcommittee 42 of the two organizations' Joint Technical Committee (JTC) 1. The ISO/IEC JTC 1/SC 42 process is in its early stages and has produced a number of drafts currently being developed in committee around AI topics including ISO/IEC WD 22989: Artificial intelligence concepts and terminology, and ISO/IEC WD 23053: framework for artificial intelligence (AI) systems using machine learning (ML). This ISO framework is built on previous ISO standards such as ISO/IEC 22989. It digs deeper into machine learning. It also reshapes AI related concepts into a framework and explains how machine learning algorithms are developed. This standard is widely used among experts and non-practitioners. This standard has many advantages:

- It makes more advanced use of AI [36];
- Machine learning features like accuracy and explainability are interpreted and set in an international frame [37];
- It gives AI standardization for policing software explored [38].

Therefore, ISO/IEC 23053 emerged to give standardization for machine learning of AI. The ISO/IEC 23053 includes stages like: task (problem definition), model, data, software tools and techniques [25]. Moreover, ISO/IEC 23053 designed the machine learning framework consisting of AI system life cycle and machine learning pipeline as shown in Figure 5 previously. ISO/ IEC 23053 standard adds regulations to the properties of AI like risk management, security, explainability, and fairness [25].

AI is adopted worldwide and in various industries like health [15] manufacturing [16], and marketing [24]. It was proved valuable during the COVID 19 pandemic. The emergence of ISO/IEC 23053 is indeed significant, as it provides a standardized framework for AI, which is crucial for ensuring the responsible and effective use of AI technologies. ISO/IEC 23053 also introduces a machine learning framework that includes the AI system life cycle and machine learning pipeline. This framework likely helps decision makers in organizations structure their AI projects and ensures that they follow a systematic approach from problem definition to deployment.

Figure 6 consists of AI life cycle along with machine learning ML pipeline as described by the new ISO/ IEC 23053 standard. This standard adds some properties and regulations to AI concerning risk management, governance, security, privacy, accountability, transparency, explainability, safety, resilience, robustness and fairness. Figure 5 shows that AI life cycle is made up of seven stages which are inception, design and development, verification and validation, deployment, operation and monitoring, re-evaluate, and retirement. These stages are mapped into this paper's research framework. Moreover, the ML pipeline cycle consists of six stages, which are data acquisition, data preparation, modeling, verification and validation, model deployment and operation.

ISO/IEC 23053 includes several important aspects that should be considered throughout the AI life cycle and ML pipeline, like risk management, governance, security, privacy, accountability, transparency, explainability, safety, resilience, robustness, and fairness [23]. These aspects are crucial for responsible and ethical AI development and deployment.

ISO/IEC 23053 seeks to promote responsible and ethical AI development and deployment. This standardization effort helps establish a common framework for AI development that can be adopted by organizations and industries to ensure the reliability, safety, and fairness of AI systems.

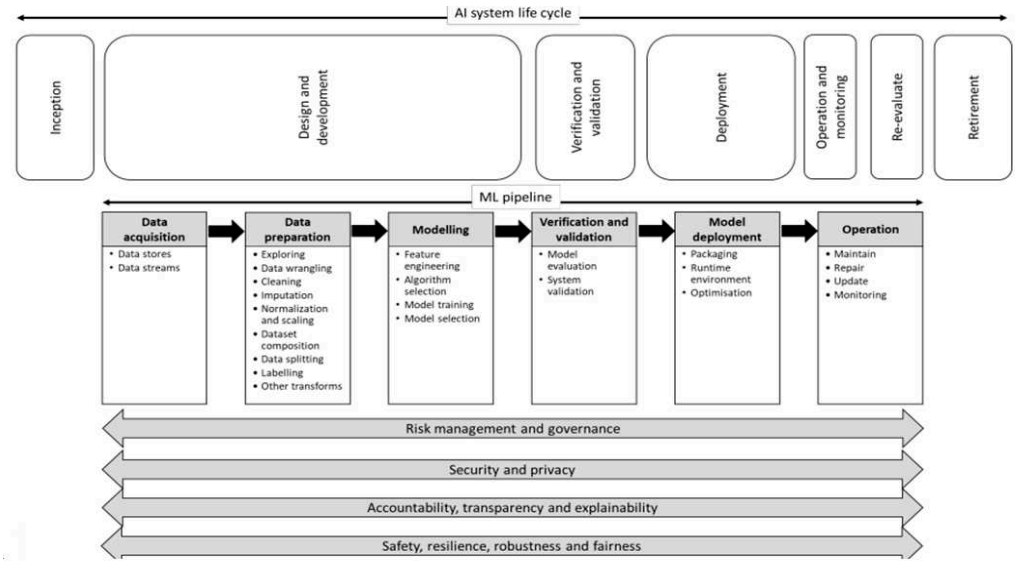

Figure 6. ISO / IEC 23053 AI life cycle [23].

After reviewing literature papers about business excellence models (EFQM), artificial intelligence and machine learning, gaps are introduced. The main gap lies in integrating artificial intelligence into EFQM business excellence model to enhance operational excellence. Few papers were found studying the effect of artificial intelligence on operational excellence. Some papers mentioned the AI effect on economy, and marketing. Dirican C. stated the effects of artificial intelligence on business and economy. He also mentioned the human replacement by robots. The AI invasion will result in higher rate of unemployment, which will affect the economy [17]. So, this research paper's framework:

- Enriches the knowledge body by injecting AI into business excellence models (EFQM);
- Enhances operational excellence;
- Is applied to any sector worldwide;
- Saves time and money before applying to EFQM excellence award.

2.2. Research Methodology

AI is injected into business excellence model (EFQM) to predict future EFQM results. This integrated framework enhances operational excellence in public and private organizations.

Figure 7 shows the outline adopted in this journal paper. EFQM scores were collected and arranged into datasets. These datasets will be the input of an AI framework (using k-means clustering where k=2). The AI model used is following the ISO/ IEC 23053 standard. The datasets will train the algorithm to predict future results. Using this framework contributes to the knowledge body and enhances the operational excellence in any organization.

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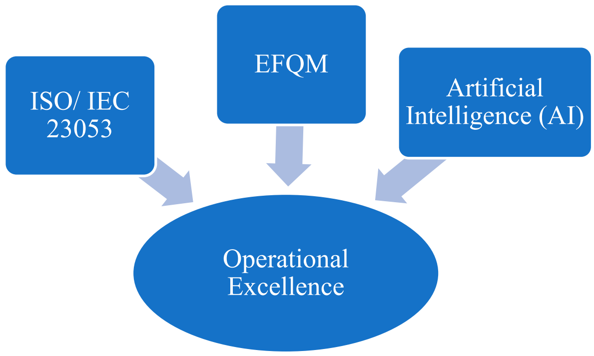

Figure 7. Outline for predicting operational excellence.

After preparing the datasets, python is used to train, test, and validate the predicted EFQM score results then accuracy scores are calculated for the k-means clustering used.

The design science research methodology is the methodology used in this paper research. Wieringa explained the design science methodology as it is the creation and search for artifacts in context. Artifacts communicate with any difficulties found in the context or overall environment to ensure continuous improvement [39]. The two types of research problems in design science are design problems and knowledge questions.

Design problem research aims to create an artifact that will improve a problem context, taking into account stakeholder goals. Multiple solutions for a specific design research problem are possible and the effectiveness of these solutions is evaluated with respect to stakeholder goals. Knowledge question research attempts to answer an analytical or empirical knowledge question about an artifact without necessarily changing the artifact itself. Knowledge questions can have multiple answers and involve a level of uncertainty. The answers to a knowledge question have to be evaluated by truth, which is independent from the stakeholders' goals [39]. Analytical knowledge questions are answered by analyzing concepts, while empirical knowledge questions are answered by collecting and analyzing data [40].

The framework of the design science research methodology is represented in Figure 8 [39]. As shown, the design science framework includes a social context, which consists of stakeholders such as users and operators. In my paper, the social context is any organization following the EFQM scoring standard. The goals are set based on stakeholder (any government/ private entity) requirements and the outcome of the research is consequently used by the stakeholders. The framework also includes the knowledge context consisting of the current knowledge of the design, specifications and practical experience. This knowledge context is used as an input to the design research on existing designs or existing answers to knowledge questions. An example is the input of operational excellence given by any organization to predict future results using AI techniques. The results of the design science may enrich the knowledge context with new answers, new problem-solving knowledge and new designs. In my research, this is shown in the output of the AI predicted results. The following figure shows the design science methodology framework in general and Figure 9 shows the design science methodology as it is applied to my research. Figure 10 shows the research methodology flowchart

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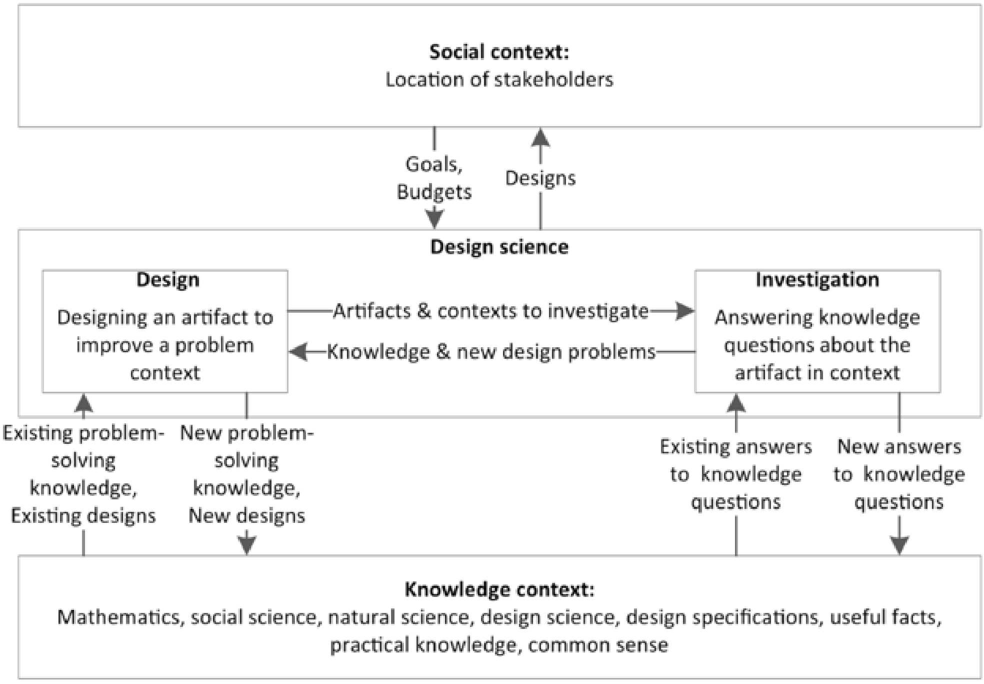

Figure 8. Design science framework.

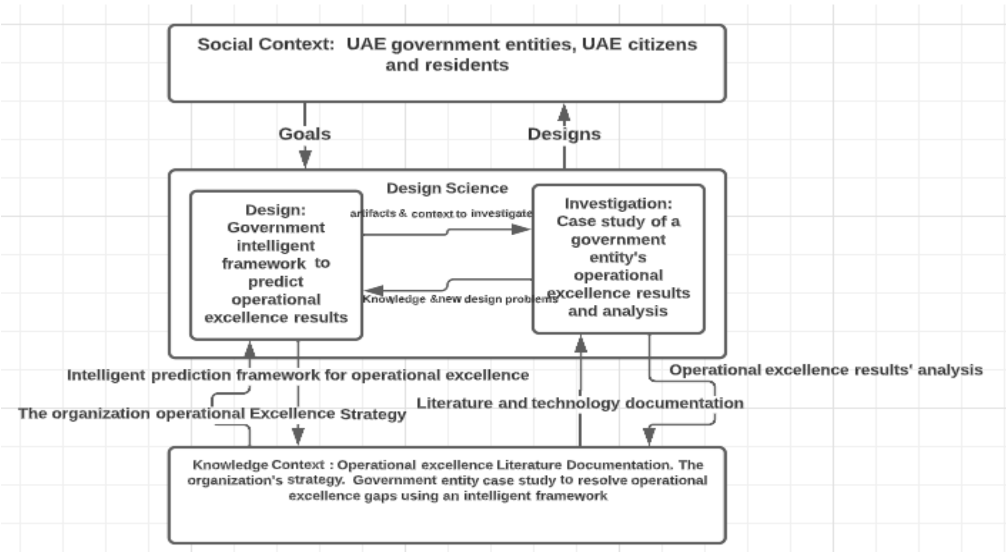

Figure 9. Design science framework applied to this paper.

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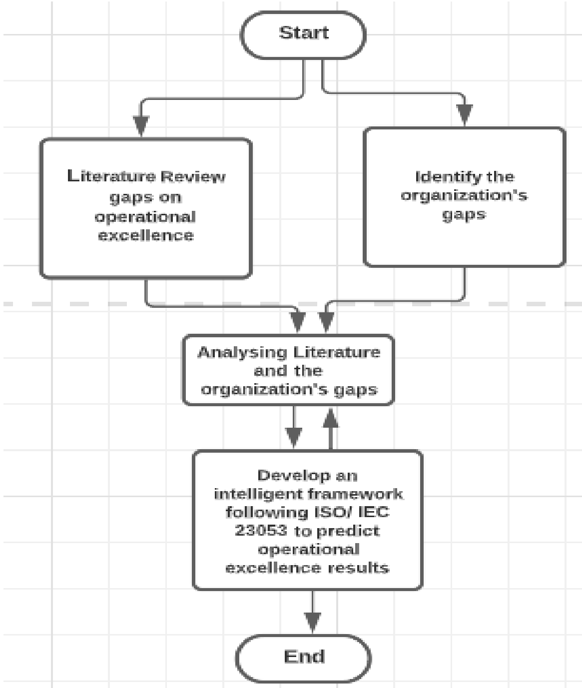

Figure 10. Research methodology flowchart.

2.3. The integrated AI framework

Figure 11 shows the state machine diagram. It represents the integration of AI with EFQM to achieve operational excellence. This framework also follows the ISO/ IEC 23053 standard in its stages. It starts with the data acquisition state, data preparation, modelling, verification and validation, operation and monitoring, comparison, feedback, and retirement states. Each of these stages is fully discussed in Figure 12, Figure 13 and Figure 14. Figure 11 shows AI and ML techniques (k-means clustering k=2) that are mapped with ISO / IEC 23053 standard to form an intelligent framework to predict operational excellence. Decision makers inject EFQM input results into the framework. The k-means clustering technique used in the framework applies the ISO/IEC 23053 standard as follows: the data acquisition state, data is collected and cleaned. While, the design and development modelling stage in ML life cycle refers to the modelling phase of the above framework. Data in this stage is trained. The verification and validation phase of AI life cycle is applied to test and validate the data. In the model deployment phase, the unsupervised ML k-means clustering is applied where k=2. Accuracy results are calculated to validate results. K-means clustering is following the ISO/IEC 23053 standard in the model deployment phase. In the operation phase, the accuracy of the AI system is monitored and the final score is returned. Two outputs are resulted either “High” or “Low”. If the output is “High”, then operational excellence is achieved where the AI model can be in the retirement phase, else the output will be “Low”, and then the AI model is in the re-evaluation phase. When the output is low, the framework searches for lowest score criteria in the comparison state and returns the inputs with the same lowest score. In the feedback state, the AI framework gives suggestions to improve the organization’s weakness points. Now, the framework moves into the termination state. Decision makers can inject input scores again into the framework until the output is high and operational excellence is achieved.

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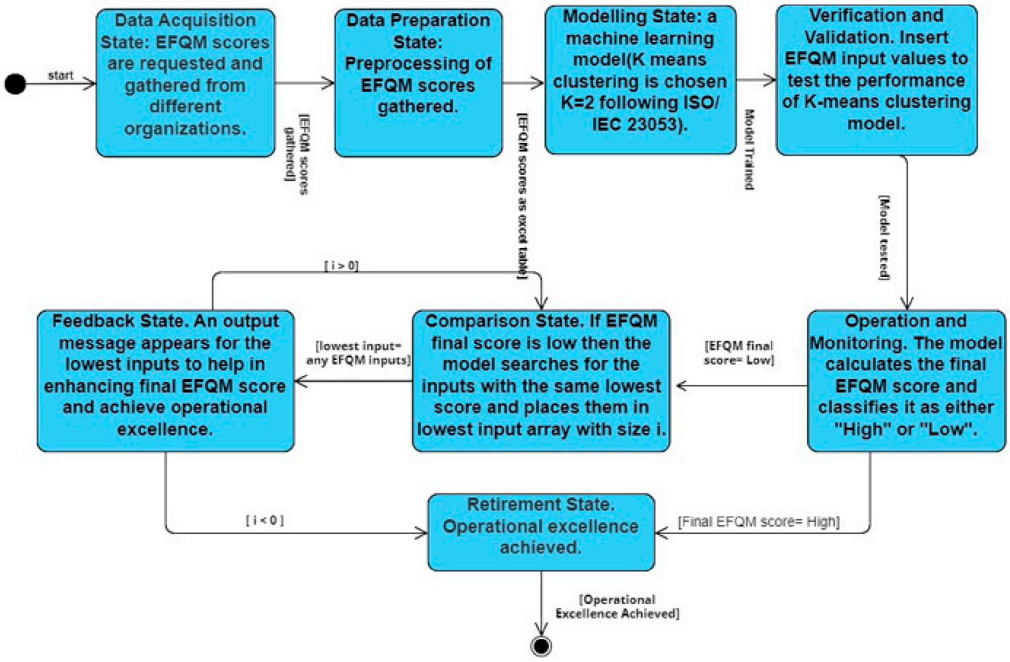

Figure 11. State machine diagram of the AI integrated framework.

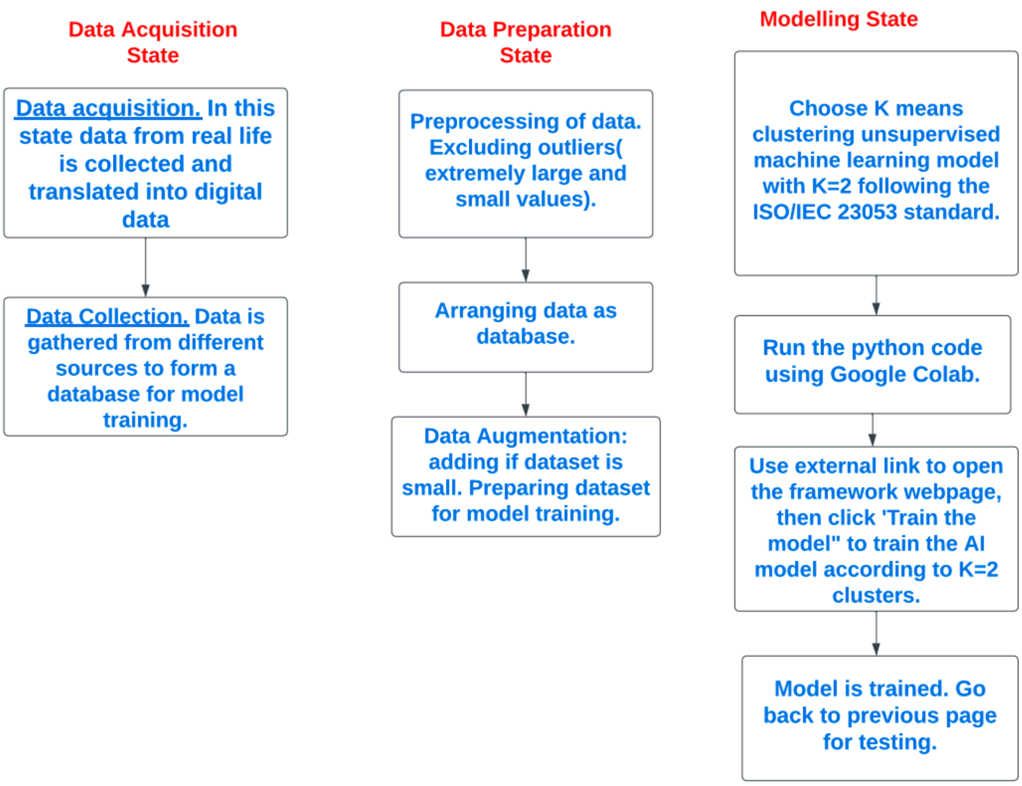

Figure 12. Data acquisition, data preparation, and modelling states.

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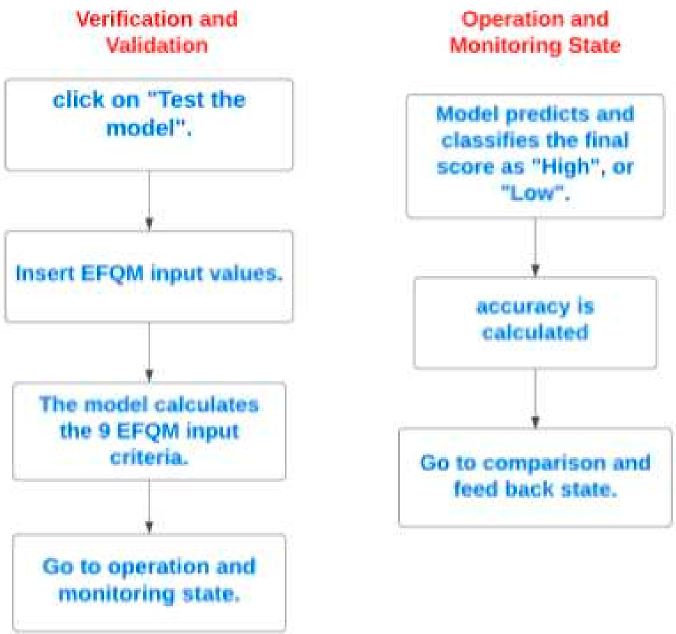

Figure 13. Verification and validation, operation and monitoring states.

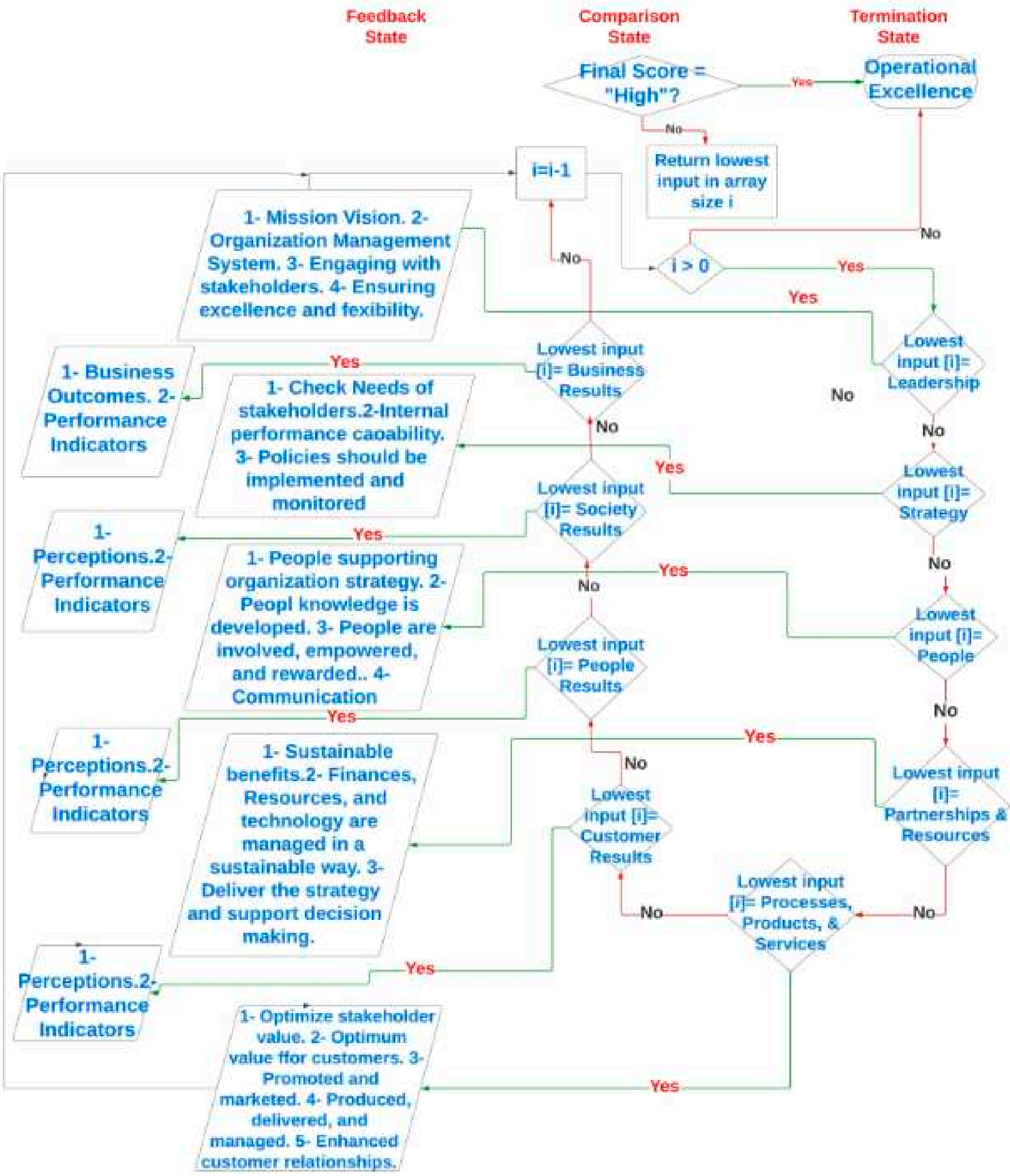

Figure 14. Comparison, feedback, and retirement states.

Despite all AI benefits, however, it faces certain ethical, moral, social, and security obstacles. So, ISO developed standards to maintain healthy development of AI [41]. AI drawbacks can affect human privacy and development [41]. Solution of such problem can be the integration of ISO 26000 at early stages of the AI system. In the above framework social responsibility shows when social results are measured and evaluated. Some suggestions are given to improve social results such as enhancing social perceptions and performance indicators. Furthermore, AI showed reproducibility, selecting, and reporting biases [42]. AI systems can misbehave towards unreliable data making them unsafe and untrustworthy. ISO 24028 is also used to ensure AI trustworthiness [42].

3. Results and Discussions

3.1. Old EFQM Model Results

In this section, EFQM is embedded in an AI framework to predict future operational excellence final scores. The training database consists of 196 rows containing nine EFQM input dimensions for the framework. This framework takes these EFQM input dimensions from decision makers in an

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organization and predicts the total EFQM score as either 'High' or 'Low'. Organizations with low outputs will try to enhance their scores by enhancing the lowest EFQM inputs until the organizations reach a 'High' final scoring achieving operational excellence. This framework uses K-means clustering (K=2) which is an unsupervised machine learning algorithm.

Figure 15 shows the descriptive statistics generated by SPSS software to calculate the row count, minimum, maximum, mean, and standard deviation of the data set used. This dataset has 196 rows using old EFQM.

Figure 16 shows the SPSS correlation results of the old EFQM dimensions and total score. It is noticed that 'People Results' and 'Society Results' dimensions are the most correlated to the final total score. However, the 'Partnership Resources' dimension has the least effect on the final score.

	N	Minimum	Maximum	Mean	Std. Deviation
Leadership	196	9	99	48.80	20.248
Strategy	196	6	100	40.27	19.660
People	196	3	100	39.26	23.988
Partnership Resources	196	1	100	37.70	20.555
Process, Product, and Services	196	1	97	38.53	21.996
Customer Results	196	2	100	29.96	24.328
People Results	196	3	98	30.57	28.527
Society Results	196	1	99	38.69	26.599
Business Results	196	3	99	46.40	19.596
Total Score	196	205	972	397.85	203.663
Valid N	196				

Figure 15. SPSS descriptive statistics for old EFQM (196rows).

Variable	Variable2	Correlation	Count
BusinessResults	TotalScore	.430	196
CustomerResults	TotalScore	.497	196
Leadership	TotalScore	.513	196
PartnershipResources	TotalScore	.337	196
People	TotalScore	.501	196
PeopleResults	TotalScore	.821	196
ProcessProductandServices	TotalScore	.591	196
SocietyResults	TotalScore	.675	196
Strategy	TotalScore	.484	196

Figure 16. SPSS correlation of EFQM dimensions and the total score.

Figure 17 is a Google Colab heat map simulation showing the same results. The highest correlation is between 'Society Results' dimension and 'People Results' and 'Customer Results' dimensions with values 0.6 and 0.5 respectively.

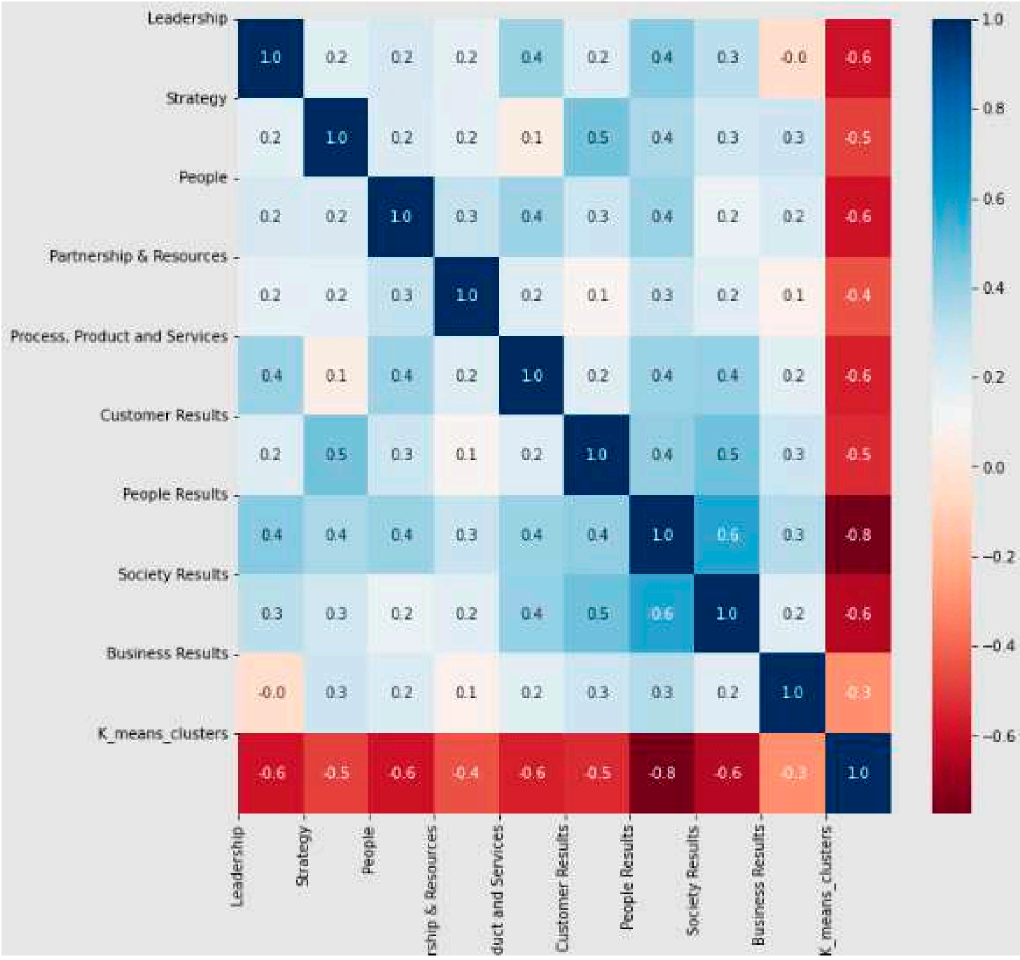

Figure 17. Google Colab simulation for studying EFQM input correlation.

Figure 18 shows the elbow chart simulated from Google Colab when old EFQM is used. The best number of clusters should be chosen just when the graph starts to be steady. Therefore, the best number of clusters k for this dataset is between 2 and 6. However, Figure 19 shows the accuracy to be 86.73 (k=2).

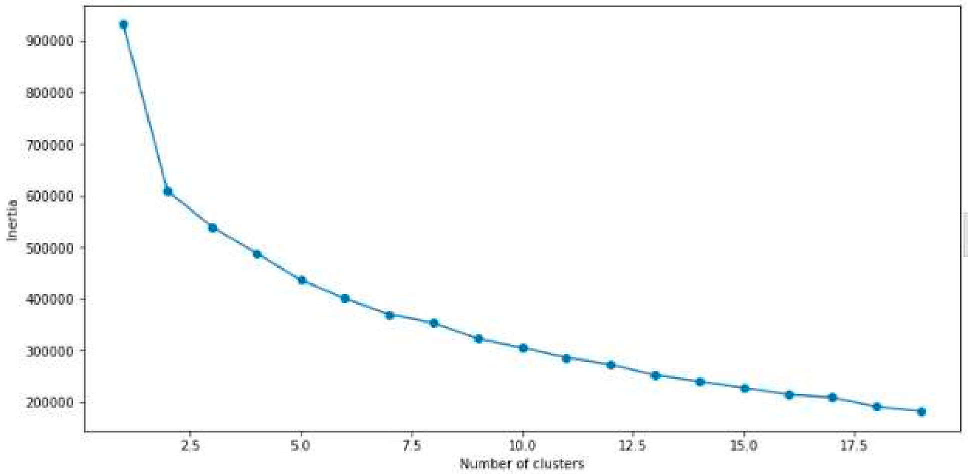

Figure 18. Elbow diagram to determine k value in old EFQM.

```
[63] accuracy = accuracy_score(y, predicted_labels)
     print('The Kmeans model accuracy is ', accuracy*100)

The Kmeans model accuracy is  86.73469387755102
```

Figure 19. Accuracy for 196 rows dataset.

The framework of this research paper takes EFQM results from an organization (196 rows dataset) and injects it with k-means unsupervised machine learning to predict operational excellence. The k-value used is 2 due to accuracy problems. The algorithm is implemented via Google Colab, which is used to design a code to train, test, and predict operational excellence given a dataset. First, libraries are defined. Then the 196-row database is imported and read. After the code is run, a link will appear for decision makers to use which will forward them into a new tab where they will be asked to train then test the model. The output is classified as 'High' if the final score is greater or equal 500; otherwise, it is 'Low'. The algorithm generates a graphical user interface webpage to train, then test the data as shown in Figure 20.

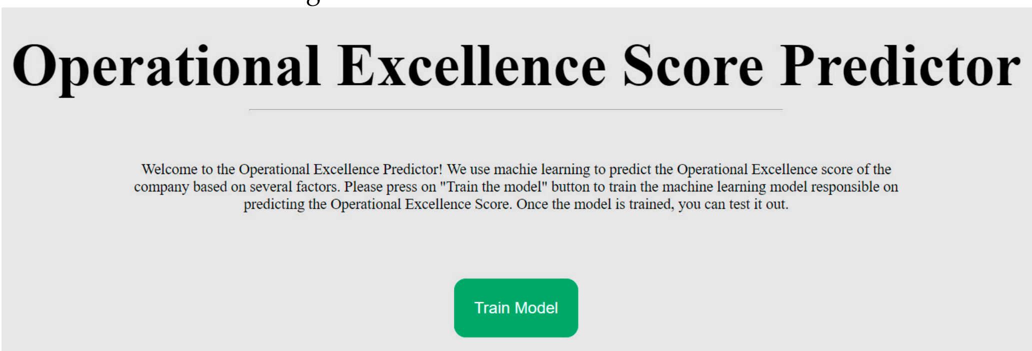

Figure 20. Train the model.

First, data is trained using the imported dataset with k-value =2 as Figures 20 and 21 show. Then, decision makers need to test the model by importing the input EFQM dimensions' criteria. Final scores are predicted and either message of 'High' or "Low" is generated. If the result is "high", the webpage shows a message that you reached operational excellence as shown in Figure 22; else, it returns the inputs with the lowest score and gives suggestions to decision makers to improve their final score as shown in Figure 23.

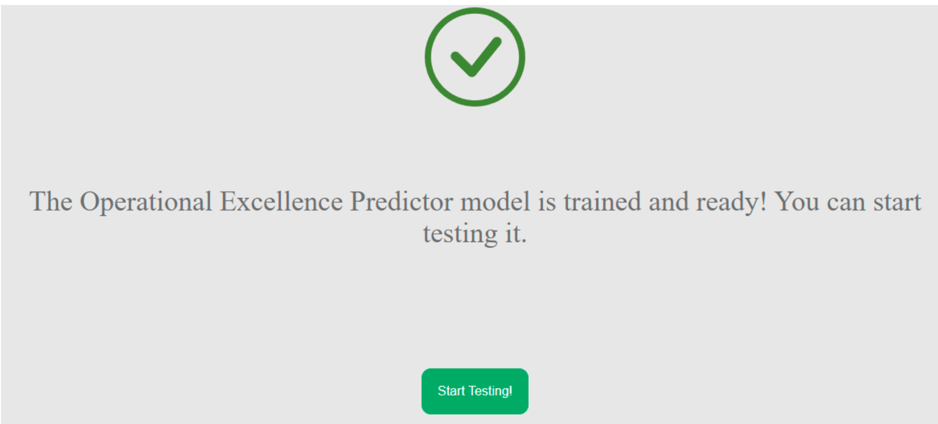

Figure 21. Model trained output message.

Now, the case of more than 2 dimensions having the same lowest input score is studied, and is shown in Figures 24 and 25. Leadership, people results, and society results have the same lowest input score =10. The output returns the lowest three dimensions with recommendation for each to improve.

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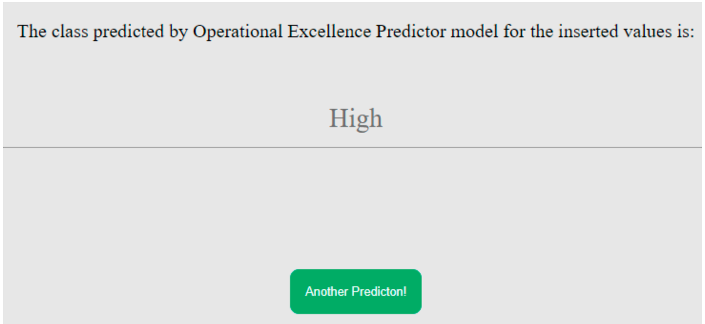

Figure 22. 'High' output.

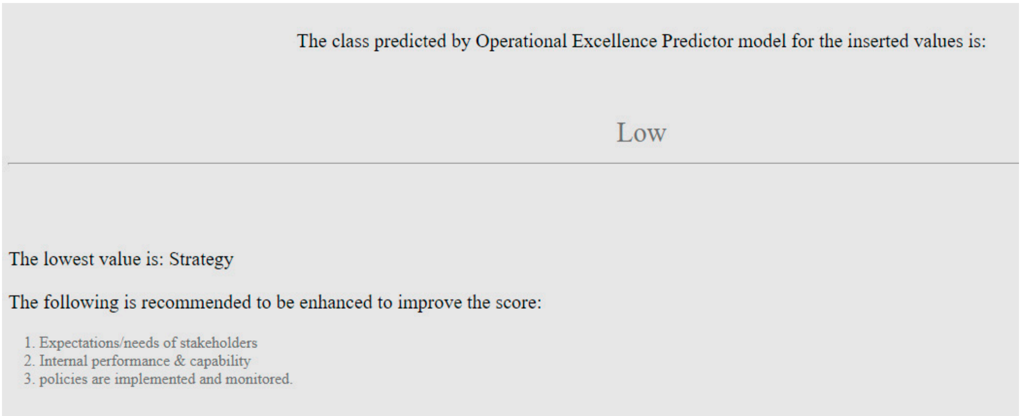

Figure 23. 'Low' output.

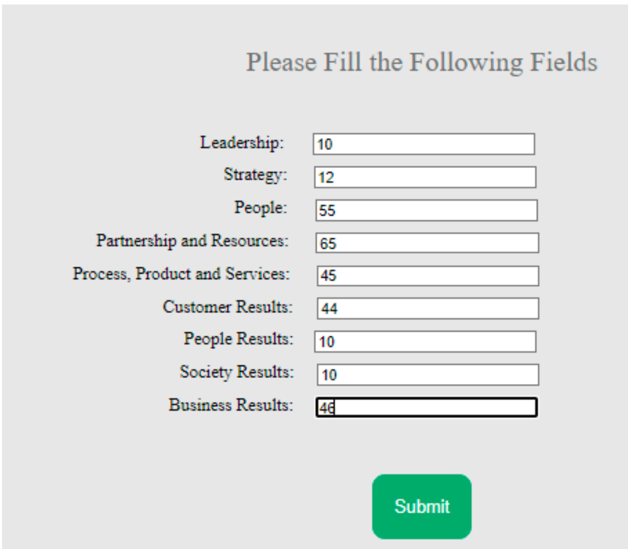

Figure 24. Three equal 'Low' inputs.

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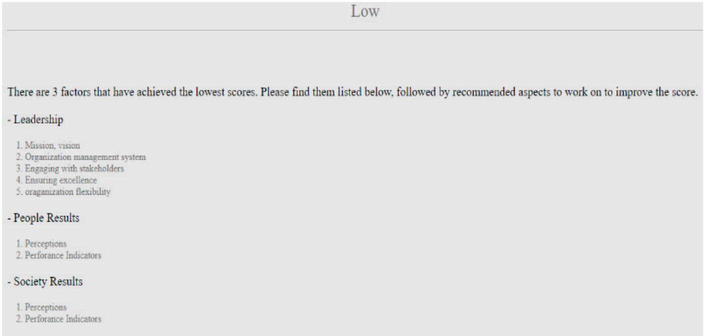
Low

There are 3 factors that have achieved the lowest scores. Please find them listed below, followed by recommended aspects to work on to improve the score.

- Leadership

1. Mission, vision
2. Organization management system
3. Engaging with stakeholders
4. Ensuring excellence
5. oraganization flexibility

- People Results

1. Perceptions
2. Perforance Indicators

- Society Results

1. Perceptions
2. Perforance Indicators

Figure 25. Three 'Low' outputs.

3.2. New EFQM Model Results

Figure 26 shows the elbow diagram when new EFQM is used to choose the suitable k value for k-means clustering algorithm, which is where the curve starts to decrease, and before it is steady. In this case, k can be chosen to be between 2 and 5. K=2 is chosen for accuracy issues. Figure 27 shows the correlation between new EFQM dimensions. This figure shows that new EFQM dimensions are more correlated to each other than the old EFQM dimensions. There are many strong correlations (0.9) as between 'Organizational Culture and Leadership' and 'Purpose, Vision & Strategy'. Figure 28 shows very low accuracy when using the new EFQM model and applying the k-means clustering. This value remained low even when k value is changed.

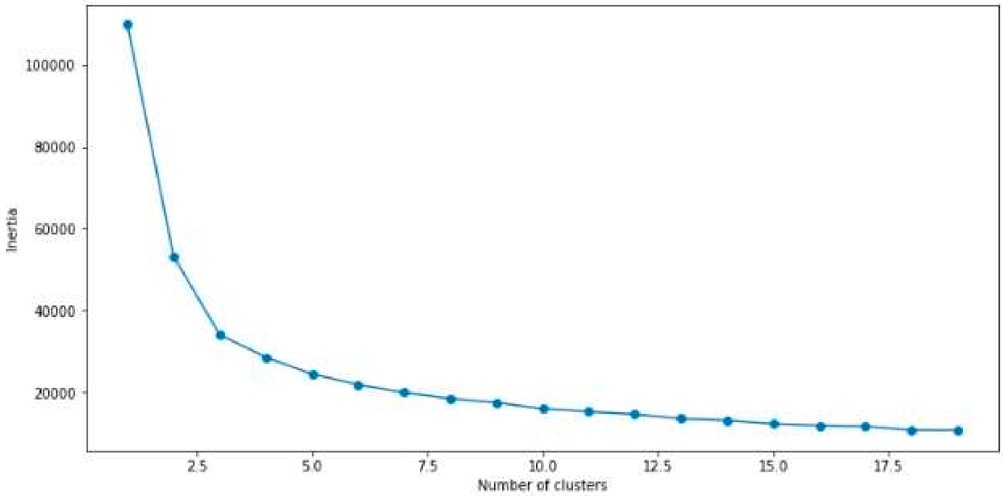

Figure 26. Elbow diagram for determining k value for new EFQM.

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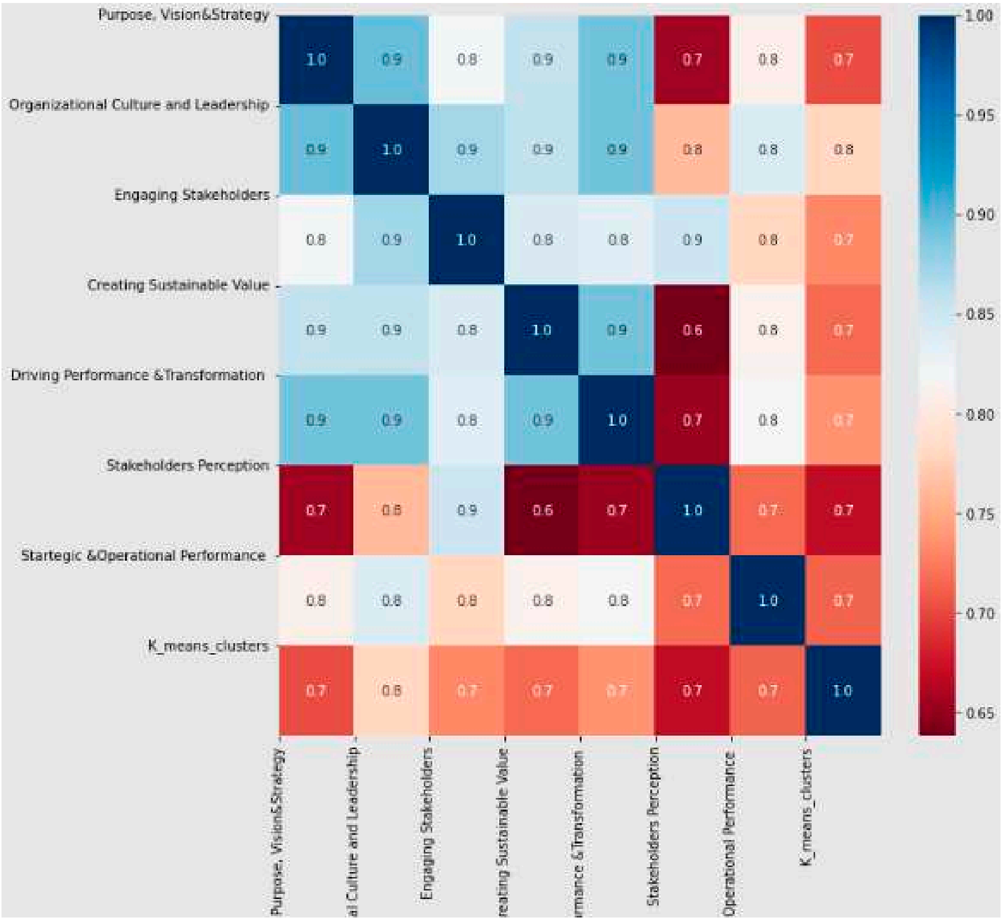

Figure 27. The heat map for new EFQM dimension correlation.

```
[100] accuracy = accuracy_score(y, predicted_labels)
      print('The Kmeans model accuracy is ', accuracy*100)

      The Kmeans model accuracy is  26.035502958579883
```

Figure 28. Accuracy for new EFQM model.

4. Conclusion

4.1. Significance

The basic significance of this research is to improve the operational excellence in public and private organizations. This research is innovative since it adds to the knowledge body a new concept of injecting AI following the ISO/IEC 23053 standard into EFQM leading to operational excellence. This can be of great value for organizations seeking to enhance their performance and attain recognition in the field of quality management.

4.2. Future Studies

This research paper guides the way for future studies. Benchmarking between different business excellence models can be studied when using different machine learning techniques. Quality 4.0, or new EFQM can be also used to predict operational excellence using different AI techniques. The model can be applied to different industries worldwide, then benchmarking can be done.

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