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A Framework for the Characterization of Aviation Construction Projects: The Case of UAE

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Abstract: This article contributes to the existing literature by modeling and automating the learning process from previous aviation construction projects (ACPs) using artificial intelligence tools, where it will be easier to characterize aviation construction projects and identify the specifications of different aspects of the projects throughout their entire life cycle. An artificial intelligence (AI) framework is proposed for the categorization of aviation construction projects using different machine-learning (ML) methods with a focus on the UAE as a source of data. Airport construction projects have been seen to share a good deal of similar attributes, which should simplify the decision-making process regarding layouts, design, equipment, labor, budget, complexity, etc. However, the gap in reality is that the huge and scattered sources of data, project specifications, characteristics, and the knowledge from past projects are not utilized in an automated way that could simplify the navigation through projects for better future decision-making. The utilization of AI/ML tools is expected to be useful here in order to reduce the revisions of design and construction rework by classifying the projects and the elements that managers need to consider. The planning, design, and construction of new projects can be improved by identifying the attributes of past projects and categorizing them according to similarities, differences, and complexities. Specifically speaking, a framework of hierarchical clustering and neural networks is integrated together to form the classification model. Upon implementing hierarchical classification and neural networks, it was found that neural networks could demonstrate remarkable classification results; the error in classification was minimal in most of the cases. The advantage of such classification is to help decision-makers utilize best practice from the groups of previous projects, which were classified using both hierarchical and neural networks models. With this classification, rework can be minimized, overhead costs may be reduced, and past best practices can be utilized.

Keywords: artificial intelligence; project management; aviation construction projects; management; machine learning; classification

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1. Introduction

Project management (PM) is about multiplexing knowledge, skills, tools, and strategies to provide something of value that will serve the needs of humans and competitive business. Project-related activities can range from software development and building construction to expanding sales into new geographical regions and markets, and much more. The primary objective of engaging in these activities is to deliver a distinctive product, service, or result that contributes positively to the overall quality and value of the product or service as a whole. Project management makes use of a variety of resources to provide something of value to the people who utilize it. The ultimate purpose of every project undertaken is to create something new, whether it is a product, service, or consequence [1,2]. Due to technological improvements and globalization, it is essential to enhance the decision-making process. Accordingly, the implementation of artificial intelligence and, particularly, machine learning can draw on the best of previous practices to enhance PM and make better use of existing data, particularly in the construction industry [3].

AI can be defined as "a machine that inputs data from the real world, processes it, and makes specific decisions as a result in order to achieve a goal". Meanwhile, machine learning can be considered as "a subset of AI which focuses on developing software, mostly algorithms that can learn to accomplish tasks by themselves without a developer explicitly telling it how to" [4]. The use of AI allows project managers to better predict future consequences and to have a better understanding of probable outcomes, which enhances the trustworthiness of their judgment. Many AI schemes tend to reduce redundant observations by discovering correlations in the data, allowing managers to focus on the most important data records [3].

According to the research in [5], PM is an example of an unintuitive problem–solution–fit. However, as the main function of AI is learning from data, applying AI in the field of PM is somewhat challenging. Because projects are not the same, each project has its unique setting and different scope of work. Highlighting this, during the life cycle of the project, different decisions are made depending on the knowledge and the experience of the project manager [6]. However, PM does not appear to be a natural application area for AI. This is because the information used in projects is not structured/arranged in a way that allows for a direct use of machine-learning techniques.

In order to facilitate the integration of AI in the field of PM, the concept of technology selection should be considered. At present, the world is full of large numbers of technologies that have and are being developed and improved very quickly [7]. Hence, organizations are always looking forward to implementing new technologies and processes to enhance the quality and efficiency of their projects in terms of reducing the cost, shortening their duration, and maintaining their quality levels. Consequently, selecting the most appropriate technology is very important and a critical task in the evaluation of projects. Looking for different and new technologies that can be used to improve efficiency or to reduce the costs or the time is a major requirement in PM [8].

Moreover, it should be noted that, due to the rapid and huge revolution of technologies, the selection of the proper technology is an important process in order to find the technology that best matches the intended application, as the selection of the right technology will help organizations and firms to sustain their position in the market and remain competitive [9]. Hence, it is essential that organizations fully understand the available AI applications before identifying cases where it is applicable.

2. Literature Review

AI in construction projects is a game-changer for the sector in terms of efficiency, safety, and creativity [10]. The several uses and effects of AI technologies, such as automated design procedures, intelligent project-management systems, and predictive analytics, are examined in this literature review. The review shows how AI-driven solutions are tackling long-standing issues, improving operational accuracy, and promoting a new age of smart building by looking at current developments and case studies. The increasing amount of research highlights how AI is transforming construction projects and establishing new performance and environmental standards [3,10].

The intersection of AI, project management, and construction projects represents a frontier where technological advancements promise significant improvements. AI enhances project management in aviation by different aspects such as schedule optimization, resource allocation, predictive maintenance, etc. [6,10]. The review in [6] examines how AI-driven tools enhance decision-making and operational efficiency, ensuring safer and more cost-effective construction of critical aviation infrastructure. Achieving cost, quality, and timely completion is paramount in aviation construction projects, where any delay or budget overrun can have substantial operational and financial implications.

2.1. Impact of AI on Project Management

Projects are found everywhere and in different sectors in which the need for proper management is imperative to deliver very professional and high-quality work. Integrating AI with project management will improve the decision-making process, where the function of AI will be to identify the crucial data that management needs to receive and prioritize for efficient use. AI and machine-learning algorithms are expected to have the ability to analyze and propose estimations on different project activities and tasks based on lessons learned from previous projects [6] and reveal the unseen patterns and correlations within the dataset [11]. Different activities in the process of project management can be automated and made more robust, such as project planning, tracking the status of different tasks, sending notifications, resource allocations, and alerting project managers on different scenarios [3,4,10].

Also, AI provides notable support based on the data provided, allowing users to produce more reliable information in accordance with their needs. The enhanced results help project managers to avoid costly mistakes in the course of project implementation [12]. In light of the above, AI plays a crucial role in enhancing rather than replacing project managers, enabling them to collaborate with AI systems, monitor performance, analyze outcomes, and manage tasks beyond autonomous capabilities [13]. Overall, AI aids in the advancement of a capital project, thereby boosting the probability of the project generating value for the organization, as well as the discovery of appropriate resource-management strategies.

However, AI adoption in project management presents challenges such as technical complexity, data-quality issues, and ethical considerations. Ensuring accurate project data is vital for the success of AI, preventing biased outcomes and errors. Moreover, a clear emphasis on data integrity and ethical standards is essential to leverage AI effectively in achieving project-management goals [6].

2.2. Aviation Project Management

The nature of activities in the aviation field is very motivating as they also expand notably over time. Thus, it is considered a challenging field. As the number of passengers, employees, and ACPs grows, there is a need to enhance the industry's capabilities, acquire new technologies, and develop new tools. Accordingly, aviation project management (APM) is becoming ever more complex and challenging as a formula to manage such projects in this industry is not yet available, where each project has its own characteristic problems and attributes that need to be considered, including cost, time, quality, reliability, redundancy, and other critical operations [14,15].

Aviation project management can be treated as a branch of project management, in which all activities should achieve their purpose regardless of the risks that might arise during the project life cycle. In addition, all projects should go through the main functions of planning, organizing, and controlling. In this context, the main aim of the ACPs is to fulfill the stakeholders' requirements in terms of the allocated time, cost, and other resources and constraints. It should be highlighted that ACPs may contain different types of projects, such as civil work, construction, new designs, expansion projects, refurbishment, and new buildings [15,16].

Project management in aviation construction projects is essential to ensure the successful execution of airport expansions and infrastructure enhancements. It encompasses strategic planning, regulatory compliance, and efficient resource allocation to minimize operational disruptions and maintain safety standards. Effective management in aviation construction projects requires collaboration among various stakeholders to deliver projects on schedule, within budget, and with minimal impact on airport operations, ultimately enhancing the overall efficiency and capacity of aviation infrastructure [17,18].

Due to the complexity and the special nature of ACPs, three main items/dimensions, which are budget/cost, time, and quality, should be realized and understood very well in order to complete the project successfully. These three objects are called the Project

Management Triangle (PMT), as shown in Figure 1, according to a study in [14]. In the aviation industry, these three elements must be considered. Here, quality could be defined as satisfying the requirements/specifications set by end-users or stakeholders, as well as monitoring the performance [16]. Providing high-quality services or goods is essential for all types of projects. Especially in the aviation industry, this objective should be met with high specifications and standards because failures in the ACPs could cause a disaster.

In view of the above, the quality of the design, engineering, operations, safety, etc., in aviation construction projects must be resilient to various threats to ensure continuous and safe operations. By integrating resilience analysis into project planning and design, aviation stakeholders can identify faults, implement measures to enhance resilience, and minimize the impact of disruptions on airport operations and services. This may involve considerations such as redundant systems, backup power sources, emergency-response plans, and infrastructure design aimed at mitigating the effects of extreme weather events or other hazards to achieve the desired quality and standards [19]. The second dimension of the PMT is the cost, reflecting the costs associated with the activities performed, workers, and materials. The third item is time, which is unique for each project and reflects the time duration needed to accomplish specific tasks. In the aviation industry, this dimension is critical, as in operations that are performed around the clock, any delays or failure will affect the reputation of the airport and result in a huge cost. Moreover, losses in this field affect the gross domestic product (GDP) of the country [14,16].

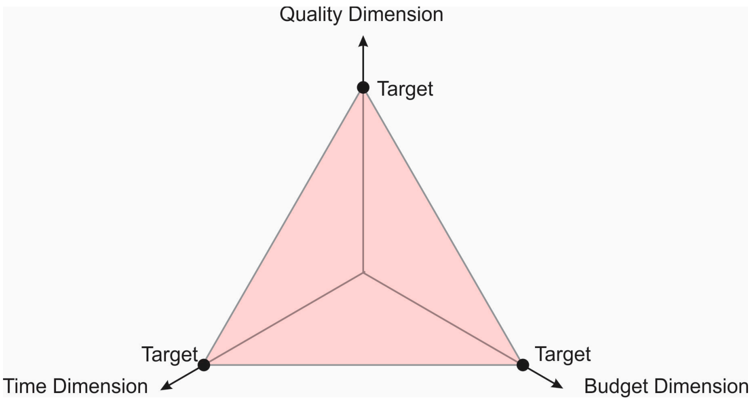

Figure 1. PMT triangle [20].

2.3. Challenges in Aviation Construction Projects

Aviation construction projects and airport expansions share a good deal of similarities from the point of view of requirements and expectations. Nowadays, construction projects in airports tend to take advantage of different existing designs and practices from around the world. It is now apparent that project designs should adhere to standard requirements, which are at the same time prone to changes due to different circumstances and emerging technologies.

Among the different types of projects in diverse sectors, aviation/airport construction projects are considered the most advanced construction projects in terms of their complexity and importance. Indeed, they are clear indicators of the economy of the country, the level of progress, and development, which contribute to the country's Gross Domestic Product (GDP). Therefore, the classical tools and technologies for managing critical construction projects in airports are no longer sufficient to address these problems. There is a need to look at emerging aspects and technologies in order to improve the airport design and processes [10].

As a consequence, the challenges associated with these types of projects are increasing in this field. Figure 2 shows some of the challenges that face the UAE's aviation construction projects [21].

Figure 2. Challenges facing airport construction projects [21].

Some of these challenges are not necessarily encountered by other countries or nations, which contribute to the distinctive part of this study as it is tailored to UAE aviation construction projects. Below is an elaboration of these challenges:

1. Ongoing or expected expansion and renewal projects: These types of projects are driven by the significant and escalating growth in the number of passengers, particularly within airport environments.
2. Tied time schedule requirements: Due to the traffic caused by the passengers and the various numbers of flights per day, the operations are critical, and the projects should be completed within the specified duration without any delays.
3. Variety of stakeholders: indicating the huge number of stakeholders and the different requirements based on the specifications set by the General Civil Aviation Authority (GCAA).
4. Wide variety of activities and functions: according to which the design concept and specification of the projects should be produced and prepared before the construction process.
5. Special systems and specifications: This reflects the number of systems used in the airport, such as security devices, electrical systems, firefighting, and alarm systems. Such systems are an additional level of complication to the design and construction process.
6. Economic returns from the sector: The aviation industry adds USD 19.3 billion to the Gross Domestic Product (GDP) of the UAE [22].
7. Security: The level of security systems is very important and should be put at the highest level.
8. Significance of the country: UAE is one of the most well-developed countries in the world, particularly in the Middle East, which serves as a hub between the East and the West.

Currently, there are many existing airport designs and layouts around the world that are considered as model creations. Such designs should be looked at when planning an expansion or renovation of existing facilities. Identifying the necessary aspects and components of a project in the early stages can save time and money and will definitely reduce design changeovers and major alterations from both the client and contractor sides.

2.4. Applications of AI in Aviation Construction Projects

The applications of AI have expanded across multiple industries, including the construction and aviation sectors. In [23], the study thoroughly categorizes AI and ML applications throughout the construction project life cycle, emphasizing their frequent use in planning and construction stages while identifying opportunities for integration in design phases. In the aviation industry, AI tools and technologies integrate various operations and processes such as pattern recognition, data analysis, and predictive maintenance. These advancements aim to enhance efficiency, reduce costs, minimize operational time, and eliminate the duplication of work, as endorsed in [6,24–26].

Different research has significant contributions by leveraging AI/ML to predict impacts of construction phases on aviation operations, enhancing efficiency, and minimizing disruptions. In [17], researchers developed an automated framework using ML techniques to classify and predict significant changes in Airport Improvement Program (AIP) projects. This framework offers stakeholders a reliable tool to identify and mitigate substantial changes efficiently, supporting improved change management for on-time, within-budget project completion and stakeholder satisfaction.

Additionally, the research paper in [18] presents a machine-learning methodology to evaluate the impact of phased construction during airport expansions on air traffic operations. It involves four stages: data collection, preprocessing, model training, and evaluation. Five models were developed and compared for accurately predicting flight delay impacts, offering efficient analysis of construction phasing plans without extensive simulations. Results indicate substantial time savings and effective decision support for minimizing flight disruptions during airport projects. This approach provides significant computational savings and assists planners in identifying optimal construction schedules that minimize flight disruptions.

Different airports around the world have considered implementing different AI tools within their operations and processes in terms of managing the huge volumes of passengers, maintenance, scheduling of flights, etc. To cite an example, Dubai International Airport has implemented different AI tools/technologies within its services, such as a self-check-in service, facial recognition for passenger identification, and other applications.

2.4.1. AI in Gate Design and Allocation

As the number of flights has increased, the number of gates has increased, too. Identifying the location and design of the gate is critical and depends on different criteria. From the design perspective, it should accommodate a specific number of passengers, and the layout should follow the passengers' and end-users' requirements. Accordingly, integrating AI within the gate design and allocation will be very helpful. Moreover, AI tools will become essential in analyzing the historical data of specific flights and provide the most appropriate design for the gate based on the expected average number of passengers derived from the data on previous flights [27,28].

2.4.2. AI in Airport Security Functions

Different AI technologies can be used in order to reveal the identity of passengers. Security scanners, facial recognition, and biometric identification are AI tools that can assist in accelerating the check-in and documentation processes. Moreover, integrating cameras within security areas and tracking the movements are additional security functions. For example, the security scanners in the airport contain AI/ML technologies that can detect any type of violation in baggage and trigger an immediate alarm [24,27,28].

2.4.3. AI in Predictive Maintenance

AI in predictive maintenance utilizes machine-learning algorithms to analyze data from sensors and historical maintenance records in order to predict equipment failures before they occur [29]. In the aviation industry, maintenance is critical as any shortage or failure in the equipment will cause disturbance and may affect the airline operations. Predictive maintenance is a type of proactive maintenance, concerned with monitoring the condition and status of equipment to predict when it may fail so that it can be replaced and fixed before the occurrence of the failure. The main goal of predictive maintenance is to estimate when certain equipment or a particular system may become faulty. Predictive maintenance uses condition-monitoring tools, along with other techniques, in order to track the performance of equipment during its normal operation time. This is done to detect or diagnose possible defects and resolve them before the equipment of the system is at risk of failure [30,31].

The big advantage of predictive maintenance is in minimizing costs. Also, it helps to reduce the downtime of a system or equipment, which in turn helps to achieve a high level of performance at work. Moreover, it helps predict the time when a fault may develop in an asset before it occurs [32]. This is essential in the aviation industry, where all operations are continuous with round-the-clock service where the interruption of activities or failure of assets will have a negative impact on the reputation of the airport and possibly cause a major disaster. In aviation construction projects, AI enhances safety and efficiency by forecasting maintenance needs of critical infrastructure such as runways, terminals, and navigation systems, optimizing operational uptime and reducing costs associated with unexpected repairs.

3. Research Objectives

This study's originality lies in its focus on aviation project characterization in the UAE, offering unique insights into the region's aviation sector. Its tailored framework provides a novel approach to understanding project management intricacies. By categorizing projects based on similarities, it enhances efficiency, potentially saving time and costs. This innovative approach advances aviation research and emphasizes practical implications.

In particular, we will be investigating the following research objectives:

1. Gather the needed data from the existing literature and real case projects to identify the features that characterize construction projects with a focus on the aviation sector.
2. Develop a model that utilizes AI tools to match new airport construction projects with similar existing ones and group projects based on their complexities, similarities, and differences.
3. Use neural networks to determine the best number of clusters that identify the projects without sacrificing the contrast between the individual projects.
4. Validate the proposed model via real projects in order to form better decisions by looking at similar practices.

By categorizing projects based on similarities and differences using neural networks, it enhances decision-making and resource allocation, potentially saving time and costs. The paper applies several innovations:

- *AI-Driven Analysis:* Utilizes AI tools to evaluate and group aviation construction projects, enhancing analysis and efficiency.
- *Neural Network Clustering:* Employs neural networks to determine optimal project clusters, ensuring precise categorization.
- *Context-Specific Framework:* Develops a tailored framework for the UAE's aviation sector, offering region-specific insights and practical solutions.

4. Research Methodology

For this study, the main objective is to match new projects with the most similar existing groups of projects. Therefore, projects with similar features and attributes will be grouped together. Due to the huge amount of data and the complexity of dealing with them, many approaches have been established to organize such data by using different AI tools and machine-learning approaches.

In order to integrate the AI tools within the field of project management specifically for ACPs, in this study, a couple of existing algorithms and approaches will be explored. Although the field of AI is very broad and contains many different tools and technologies, each tool is designed for a specific application based on the purpose and the objective of the process. The most common AI tools and approaches are shown in Figure 3. AI includes machine learning, natural language processing (NLP), speech, planning, and robotics. These tools have different algorithms and different purposes according to the application being addressed.

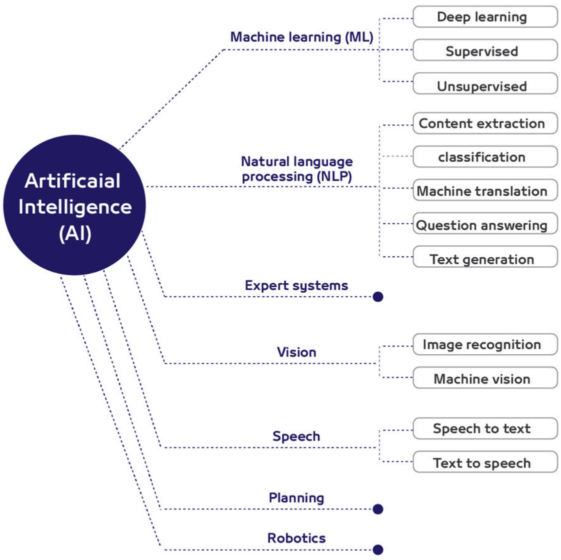

Figure 3. The tree of artificial intelligence.

Two main learning approaches are established within AI and ML: supervised learning and unsupervised learning. The main difference between both is the type of data used (labeled or unlabeled). In supervised learning, the datasets are labeled and used to train the algorithms to predict the outcome. Moreover, there are two types of categories in the supervised learning algorithms: classification and regression. In classification, the aim is to allocate the data points to a specific category based on different parameters. There are different types of classification algorithms, such as random forest, decision trees, support vector machines, etc. Furthermore, in regression, specific optimization is used to find the relationship between the dependent and independent variables [33–35].

On the other hand, it should be highlighted that the datasets used in unsupervised learning are unlabeled, which will be analyzed by the selected ML algorithm. These types of algorithms calculate unseen patterns in the datasets without human involvement [11]. Three main tasks/applications are associated with the unsupervised learning models: clustering, dimensionality reduction, and association. Clustering from the unsupervised learning approach has been selected in this study to perform the analysis. This approach was selected because it can deal with a huge amount of data with several parameters and incomplete data, and it can be used for different applications. Clustering is an unsupervised learning approach in which the data/assets will be grouped based on their similarities. Thus, objects with similar features or attributes are grouped together, or the data are divided into sub-groups that are called clusters. These clusters differ from each other according to the selected attributes. It should be highlighted that this method does not need any training data but can learn from the existing data. Moreover, there are different methods of clustering, such as latent class analysis, K-means, hierarchical clustering, partitioning methods, fuzzy clustering, model-based clustering, and many others [33,36].

Figure 4 shows the methodological steps that were followed. Conceptualizing the idea was the first step of this research, followed by conducting a literature review for identifying the characteristics of aviation construction projects. Then, a classifying procedure is performed using hierarchical clustering to identify the project groups at different HC levels. To find the best number of clusters, artificial neural networks are used for this step. Finally, testing and validation are performed using different sets of testing data.

In this study, hierarchical clustering and neural network have been selected to perform the analysis of the collected data. The study utilizes hierarchical clustering, which is a method in unsupervised learning that is used to group similar data points into clusters based on proximity. This approach allows for the identification of inherent structures within the dataset without relying on labeled data. Additionally, a neural network is employed for its ability to learn complex patterns and relationships in the data [10], offering a powerful tool for classification or regression tasks. By combining hierarchical clustering and neural networks, the study aims to comprehensively analyze the collected data, uncovering insights and underlying patterns effectively.

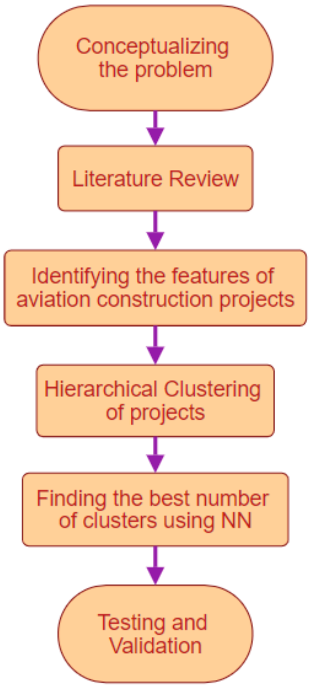

Figure 4. Methodological steps of the proposed research.

4.1. *Hierarchical Clustering (HC)*

In this type of clustering, the link between a group of data points is considered, which comes in two types: agglomerative and divisive. According to a study in [36], "In an agglomerative hierarchical clustering algorithm, initially, each object belongs to a respective individual cluster. Then, after successive iterations, groups are merged until stop conditions are reached. On the other hand, a divisive hierarchical clustering method starts with all objects in a single cluster, and, after successive iterations, objects are separated into clusters". A diagram that reflects this type of analysis is shown in Figure 5, which demonstrates how main clusters can be divided into new clusters through division. It should be highlighted that, among all the different research and studies, three algorithms were the most commonly used, and the popular methods for grouping those different assets were: latent class analysis, K-means, and hierarchical clustering [36,37].

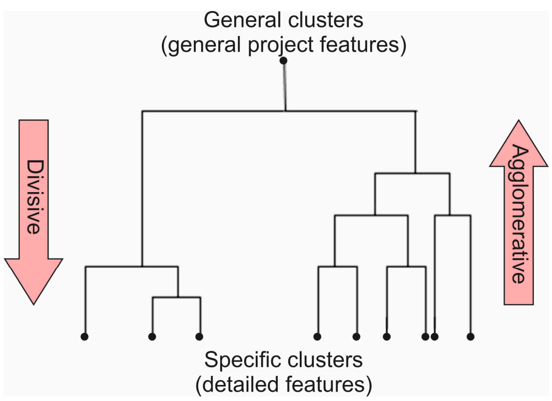

Figure 5. Hierarchical clustering.

4.2. Artificial Neural Network (ANN)

The neural network is one of the AI/ML algorithms that imitates human brain neurons to process the input data. A neural network (NN) can be defined as a set of interconnected layers, in which the inputs lead to outputs by a connected layer of weighted edges and nodes. As shown in Figure 6, the direction of the graph proceeds from the inputs through the hidden layer, with all nodes of the graph connected by the weighted edges to nodes in the next layer. This widely adopted supervised approach serves as a valuable method for elucidating the non-linear relationship between input and output data [25,38].

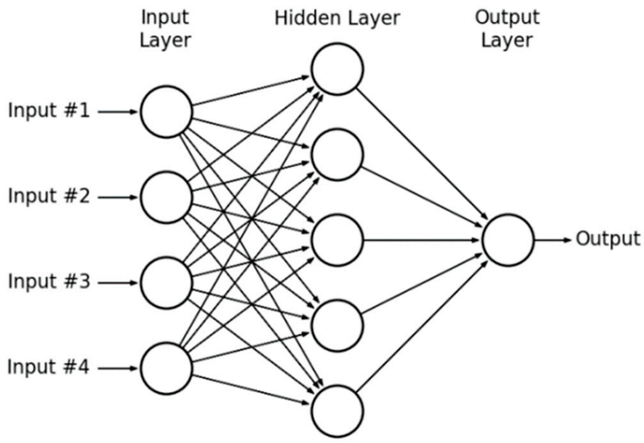

Figure 6. Radial Basis Neural Network.

5. The Attributes of Aviation Construction Projects

In this study, the literature, as well as author-designed surveys, were used to gather the attributes that are related to aviation and airport construction projects. A total of 42 attributes were collected first, then an inclusion/exclusion criterion was applied to filter the attributes to select the most applicable ones for all the available projects. Filtering was based on eliminating/merging attributes with close subject matter and keywords as follows:

- Attribute Collection: Initially, 42 attributes related to aviation and airport construction projects were gathered from the literature and author-designed surveys.
- Inclusion/Exclusion Criteria: A set of criteria was applied to filter these attributes, aiming to identify the most relevant ones for the projects in question. This process involved assessing the relevance and applicability of each attribute (e.g., some of the attributes were very specific, unique, and could not be applicable for all ACPs).
- Final Selection: After applying the criteria, 31 attributes were selected as the most applicable for accurately describing aviation construction projects. The final set of attributes and their description are illustrated in Table 1.

Table 1. Aviation Project Attributes.

Attributes	Measures/PI Project's Indicators
Project size	Project size refers to the scale of a project, quantified based on its application within a single or multiple regions, providing a comprehensive assessment of its geographical reach and scope.
Design duration	The period required for the design phase, measured in days.
Planned Construction duration	The anticipated time frame for construction as outlined in the project plan, measured in days.
Actual construction duration	The real time span taken for construction, measured in days.

Table 1. *Cont.*

Attributes	Measures/PI Project's Indicators
Project complexity level	In project management, the term "complexity of projects" refers to the complicated and multidimensional nature of the activities, objectives, and variables that are part of a project. Determining the complexity level of a project involves assessing various factors that contribute to its overall complexity, in terms of high, medium, and low.
Location	Indicated by "Indoor" or "Outdoor"
Sustainability	There are various sustainable design principles that could be considered in the projects in order to ensure that these projects are environment friendly and efficient. In this attribute, the projects will be divided as follows: 1. Environmental Sustainability, 2. Social Responsibility, 3. Economic Viability.
Project Scope definition	Four categories will be defined for this indicator, as follows: 1. Expansion 2. Refurbishment/Rehabilitation/Redesign/Upgrade 3. Repair and Maintenance 4. Replacement
Design from scratch	A binary indicator that determines if the scope of work includes redesign from scratch
Amendments on existing design	Determine if the scope of work is only modifications on the existing one.
Level of interior design required	The level of interior design in airport construction projects can vary based on factors such as budget constraints, project objectives, targeted users, and overall design vision. This indicator will be measured in terms of high level, medium level, and low level based on the required level of interior modifications in these projects.
The project involves utilizing Building Information Modelling (BIM) for design and construction	BIM reflects digitally the detailed building (3D computer model). It provides an indication of any conflicts and clashes before starting the real construction work. This model helps spot and fix problems at early stages, saving time and money. This can be measured by the binary variable (Yes or No).
Level of technology integration in the project	Percentage of digital technologies integrated into airport operations. Examples include installing automated baggage-handling systems, self-check-in kiosks, and smart boarding gates to enhance passenger experience and efficiency. This indicator will be measured in terms of high level, moderate level, and low level of technology.
Implementation of Building Management system (BMS)	The Building Management System (BMS) functions as the control center, overseeing various aspects such as heating, lighting, and security. This can be measured by the binary variable (Yes or No).
Facility/Project Type	This includes the following categories: • Concourse Modifications • Terminal Modifications • Project Reliability Assurance • Infrastructure, Airfield and Airside Road • NAVAIDS projects (navigation systems) • Security projects
Safety requirements	The level of safety requirements in airport construction projects, whether they fall under high, moderate, or low safety requirements.
Back-up power arrangements	Since the operations in the airport are critical, some areas require an alternative power source on a temporary basis until the project or the related work is done. This indicator of back-up power arrangements is provided in terms of "Yes" or "No".
Number of labor/workers	The number of workers assigned for the respective project.
Requirement of Closure	Indicates whether the construction project requires partial or complete closure of airport facilities or operational areas during the construction phase, which is given in terms of "Yes" or "No".
Requirement of road diversion	Evaluate if the construction project requires diversion or rerouting of roads or access routes near the area of application which can be measured by the binary variable (Yes or No).

Table 1. *Cont.*

Attributes	Measures/PI Project's Indicators
Technical/Operational risks	• High Risk: Risks that have a high likelihood of occurrence and significant impact on the project's progress or outcome. • Medium Risk: Risks that have a moderate likelihood of occurrence and can have noticeable effects on the project. • Low Risk: Risks that have a low likelihood of occurrence or minimal impact on the project.
Environmental Risks	• High Risk: Risks that pose a significant threat to the environment and can result in legal issues, substantial costs, or project shutdown. • Medium Risk: Risks that have a moderate potential for environmental impact but can be managed effectively with proper controls. • Low Risk: Risks that have minimal or negligible environmental impact.
Management related risks	• High Risk: Risks that involve critical project management aspects, such as budget overruns, poor communication, or inadequate resource allocation, leading to significant project failures. • Medium Risk: Risks related to project coordination, stakeholder management, or compliance issues that may have a moderate impact on project performance. • Low Risk: Risks that have minimal impact on project management and can be easily mitigated.
Level of Accessibility Restrictions	Measures the level of accessibility in airport construction projects, which typically involves evaluating the ease of access for different stakeholders, such as passengers, airport staff, and construction personnel, to various areas within the airport in terms of Highly Restricted Accessibility, Moderately Restricted Accessibility, and Adequate Accessibility.
Requirement of consultant	Almost all projects need a consultant to work with the client and report the progress or any issues within the life cycle of project. However, some projects could be consulted by the client, along with the contractor, according to the scope and size of the project. This can be measured by the binary variable ("Yes" or "No").
Cost/budget	This indicator will reflect the cost associated with the airport construction projects in terms of very low, low, moderate, high, and very high.
Current project stage	• Design • Construction • Finished/completed
The number of different engineering disciplines required	It is a number that reflects the engineering trades that are involved in the project. This includes all related Civil/Architectural, Mechanical, Electrical, IT, Security Works, and others. In this indicator, the measure will be the number of trades/disciplines involved in the respective project.
Requirement of long lead items	Long lead items are components or materials that require a longer lead time for procurement or fabrication, often due to their specialized nature or limited availability.
Survey requirements	Some projects need to be surveyed and assessed before starting the work in order to report the current status of the area and the applicability of the scope of work. This can be measured by the binary variable ("Yes" or "No").
Stakeholders' Approval	This indicator reflects the need of any shutdown permits that might affect some system, depending on the scope of the assigned project.

By considering the aforementioned attributes, which were gathered from both the existing literature and conducted surveys, we aim to comprehensively analyze and understand the various factors influencing the subject matter so that the projects can be classified using AI classification techniques according to their similarities and differences. The proposed classification framework is anticipated to enhance efficiency, minimize the rework, and ultimately contribute to reducing the cost, as will be explained shortly.

6. Classification Model

In this model, both hierarchical clustering and neural networks were integrated to test the value of formed project groups. Figure 7 shows a general diagram of the proposed framework that will be used to show the process of assigning new projects to their closest group.

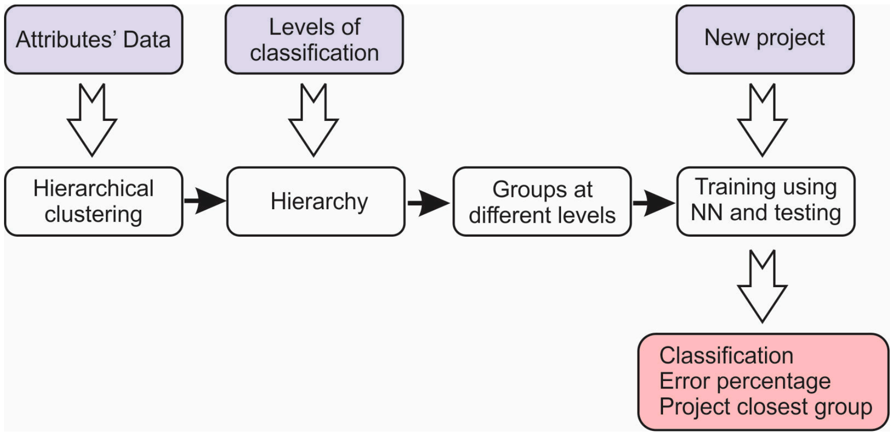

Figure 7. Framework of the proposed process (author creation).

To illustrate the diagram in Figure 7, first, the existing project attributes will be used to classify the groups using hierarchical clustering, which can be attained at different distance levels according to the dendrogram that is found by HC. For every specific distance level of the HC, a different number of clusters will result. Note that at the lowest level of the dendrogram, each project will appear in a single group. However, by elevating the level of classification, the projects will begin to form larger clusters according to similar/different attributes. For any new project, the data will be entered according to the pre-defined attributes, and then the project will be classified using both NN and HC to have it assigned to the closest group. This streamlined process facilitates the seamless integration of new projects into existing clusters, enabling effective decision-making and resource allocation within the project management framework.

The Euclidean distance measure is used in this study, which is expressed as:

$$d_{XY} = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \quad (1)$$

where d_{XY} is the distance between the two projects X and Y, and i is the index of the attributes belonging to the two projects. With this distance measure, different groups or clusters will result for different dendrogram levels. Once the clusters/groups are identified at every specific level, a neural network model that consists of input layer, hidden layers, and output layer will be built to test the goodness of classification.

To test the classification that resulted from the HC, the data is plugged in the form of clusters along with the attributes to the NN model. The neural network model in turn will test the classification that results from HC. This process will be implemented by using different proportions of training and testing data in order to identify the best number of clusters/groups based on the resulting classification tables and correct percentages for each case. Upon identifying the best parameters found using the NN, such parameters will be implemented for the final classification of any new project that may be considered in this field.

7. Data Analysis and Results

In this study, data for 20 projects was obtained from the UAE governmental entity that is responsible for overseeing airport construction projects. The project list, along with some selected attributes, is shown in Table 2. In order to prepare the data for analysis in SPSS 27.0 software, special coding techniques were employed to represent the various responses observed in the dataset. This coding system is designed to transform qualitative data, such as categorical responses or text, into numerical values that can be processed by statistical software. Table 1 provides a comprehensive guide outlining the corresponding codes assigned to each attribute for the 20 projects. These codes facilitate data entry and analysis, ensuring consistency and accuracy throughout the research process.

Table 2. Project list and a sample of the attributes. Note that the remaining attributes do not appear in the table. See Appendix A for the full list.

									Design and Technology		
Contract Title	**Contractual Duration (in Days)**	**Actual Duration (in Days)**	**Peak Manpower**	**Design Duration (in Days)**	**Project Size**	**Project Complexity Level**	**Location**	**Safety Requirements**	**the Project Involved Utilizing (BIM) for Design and Construction**	**Level of Technology Integration**	**Implementation of Building Management System (BMS)**
Project #1	360	630	170	766	1	3	0	3	1	1	1
Project #2	251	524	49	509	1	1	1	3	0	1	0
Project #3	209	598	51	576	1	2	1	2	0	1	1
Project #4	378	909	131	239	1	3	0	3	1	2	1
Project #5	144	144	38	0	1	1	0	1	0	3	0
Project #6	155	235	7	0	0	1	0	1	0	1	0
Project #7	263	263	30	126	1	3	0	1	0	3	1
Project #8	424	530	25	39	1	3	0	1	0	2	1
Project #9	659	671	17	1030	1	2	0	3	0	2	1
Project #10	786	606	4	86	1	3	1	1	0	2	0
Project #11	1045	1395	50	1089	0	3	0	3	0	3	1
Project #12	560	560	47	805	0	2	0	1	1	2	1
Project #13	209	209	25	326	0	1	0	2	0	2	0
Project #14	419	1193	20	519	1	2	0	3	0	1	1
Project #15	397	1406	26	142	1	2	0	3	0	1	1
Project #16	299	645	14	103	1	2	0	2	0	1	1
Project #17	283	518	50	825	1	3	1	1	0	2	1
Project #18	299	517	18	514	1	2	0	3	0	2	1
Project #19	879	879	82	1000	1	2	0	3	0	2	1
Project #20	885	852	9	401	1	1	1	2	0	1	0

Using the above distance measure between clusters, the projects were classified according to Figure 8, which illustrates the resulting dendrogram of the 20 selected aviation construction projects. In this study, an agglomerative approach has been applied for hierarchical clustering. This method merges similar data points step-by-step, creating a structured hierarchy, and, ultimately, leading to a clearer and more meaningful clustering result. The resulting dendrogram of the 20 selected aviation construction projects would visually display how these projects cluster together based on their similarities or differences. Each project would be represented as a node on the dendrogram, and branches would connect similar projects together based on some measure of similarity or distance. The dendrogram starts with each project as an individual cluster at the bottom. Projects are then progressively grouped together based on their similarity, forming clusters at higher levels of the dendrogram. The vertical lines in the dendrogram represent the distances or dissimilarities between clusters.

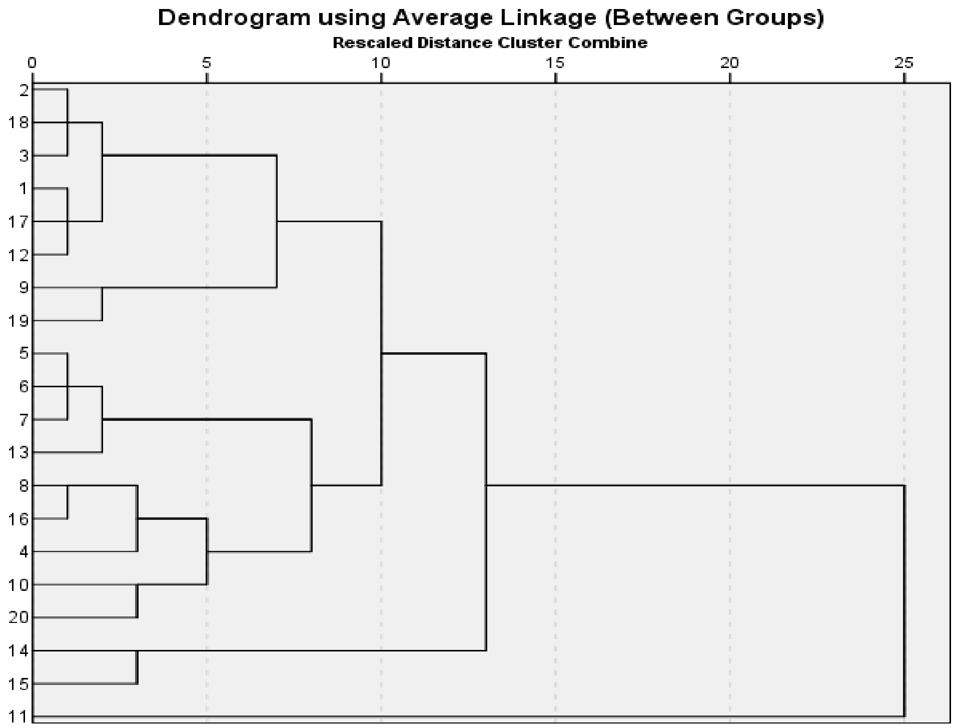

Figure 8. Dendrogram of the 20 projects.

In this context, the height at which two branches merge in the dendrogram indicates the degree of similarity between the clusters. Shorter distances between branches suggest higher similarity, while longer distances indicate greater dissimilarity. Furthermore, clusters that merge lower in the dendrogram are more similar to each other than clusters that merge higher up. Note that by presenting a vertical line at different positions on the dendrogram, different clusters can be found at each position. Figure 9 shows that nine levels (L1 to L9) will result for the collected data.

At Level 1, a total of 20 clusters will be formed, where at this level, each project is found in one separate cluster. However, at higher distance measures (i.e., levels), more grouping will be noticed and, therefore, less clusters will result, as detailed in Table 3. Note that at the highest distance, only two clusters will be formed that can separate the projects according to their similarities/differences. Overall, the dendrogram provides a visual representation of the relationships between aviation construction projects, allowing stakeholders to gain insights into project similarities, differences, and patterns, which can inform decision-making and improve project management strategies.

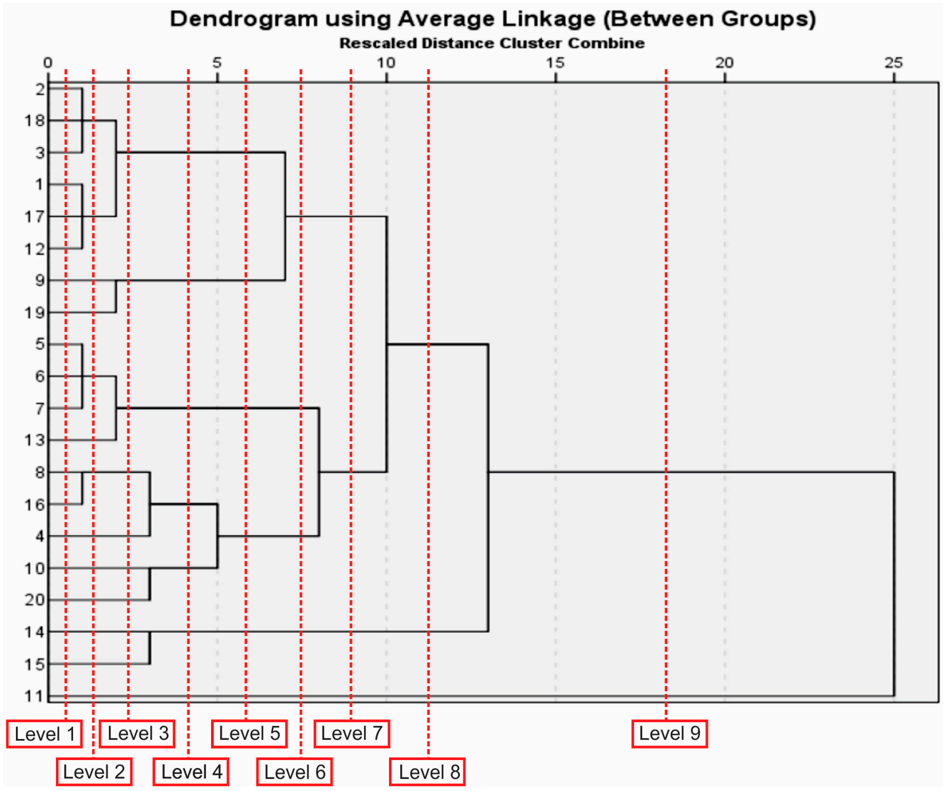

Figure 9. Agglomerative approach on the resulting dendrogram.

Table 3. Resulted groups at different levels/distances.

	Clusters at Different Levels								
Project No.	**L1**	**L2**	**L3**	**L4**	**L5**	**L6**	**L7**	**L8**	**L9**
1	17	2	1	1	1	1	1	1	1
2	20	1	1	1	1	1	1	1	1
3	18	1	1	1	1	1	1	1	1
4	6	8	5	4	4	3	2	1	1
5	12	5	3	3	3	2	2	1	1
6	11	5	3	3	3	2	2	1	1
7	10	5	3	3	3	2	2	1	1
8	8	7	4	4	4	3	2	1	1
9	14	3	2	2	2	1	1	1	1
10	5	9	6	5	4	3	2	1	1
11	1	13	10	7	6	5	4	3	2
12	15	2	1	1	1	1	1	1	1
13	9	6	3	3	3	2	2	1	1
14	3	11	8	6	5	4	3	2	1
15	2	12	9	6	5	4	3	2	1
16	7	7	4	4	4	3	2	1	1
17	16	2	1	1	1	1	1	1	1
18	19	1	1	1	1	1	1	1	1
19	13	4	2	2	2	1	1	1	1
20	4	10	7	5	4	3	2	1	1
No. of groups	20	13	10	7	6	5	4	3	2

As a remark, by having higher number of clusters, more discrimination between the projects is imposed, forcing higher distinguishability between the projects, while a low number of clusters entails less discrimination and more emphasis on the similarities.

One issue that arises from the HC is the best number of clusters that can be found using the neural network model. By integrating the HC with NN, one can suggest the good number of clusters that best classify the projects. To do so, each column ins Table 3 that represent a dependent variable is used for a separate NN model. The construction of NN for every column will yield a classification table that shows the percentage of the correct prediction of each project that matches the HC classification. The column that demonstrates the lowest erroneous classification will yield the best number of clusters.

In SPSS, multilayer perceptron function is implemented for the NN model. Here, the input layers resemble the different attributes' values, the hidden layer represents the process, and the output layer informs the resulting classification.

To identify the correct percentage in the classification table, different proportions for training and testing data have been used, as shown in the table header. For instance, 18-2 means that 18 projects are used for training and 2 for testing. The percentages of correct predictions are shown in Table 4.

Table 4. Classification table for prediction using neural networks.

No. of Groups	Training to Testing Ratio							Average
	18-2	**15-5**	**10-10**	**5-15**	**14-6**	**13-7**	**12-8**	
G20 *	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
G13	66.7%	100%	80%	100%	100%	100%	100%	92%
G10	100%	75%	85.70%	100%	100%	100%	100%	94%
G7	100%	100%	100%	60%	66.70%	100%	66.70%	85%
G6	100%	100%	87.50%	100%	100%	100%	60%	93%
G5	50%	80%	60%	80%	50%	100%	85.70%	72%
G4	100%	75%	66.70%	100%	85.70%	88.90%	100%	88%
G3	100%	100%	100%	100%	100%	100%	100%	100%
G2	100%	100%	100%	85.70%	100%	100%	100%	98%

*: Note that when each project is considered as a separate group, no clustering analysis is required.

Figure 10 shows that the classification using only three clusters (G3) demonstrates the highest average of correct predictions. Therefore, three clusters should be the suitable number for this set of projects as it demonstrates 100% of correct classification. This choice is justified by the understanding that an increase in the number of groups amplifies the contrast between the projects, thereby posing challenges to the classification process of projects. On the other hand, as the number of groups decreases, the contrast between the projects is less emphasized while there is a greater focus on the similarities, as illustrated in Figure 11.

The integration of AI techniques, such as hierarchical clustering and neural networks, not only enhanced the analysis of the collected data but also facilitated the practical application of these insights. Specifically, by utilizing the patterns and structures uncovered during the analysis phase, the system is equipped to efficiently assign new projects or data to the most appropriate category or group.

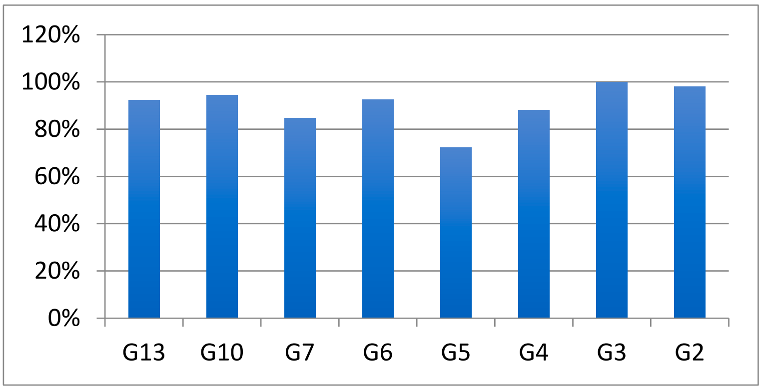

Figure 10. Correct percentage at different number of clusters.

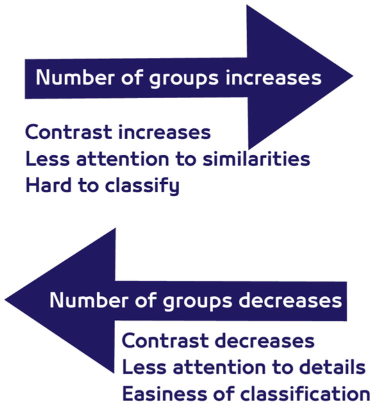

Figure 11. Relationship of groups' numbers.

For instance, the hierarchical clustering technique organizes the existing data into clusters based on similarity, establishing a framework for classification. When a new project or dataset is introduced, the system leverages this framework to identify the closest matching cluster, thereby assigning the new data to the most relevant group. Similarly, neural networks, with their ability to learn and recognize complex patterns, contribute to the accurate classification of new projects. By training the network on the existing dataset, it becomes adept at discerning subtle relationships and features that determine the categorization of projects. When presented with new data, the neural network can swiftly evaluate its attributes and assign it to the appropriate category based on its learned knowledge.

In this way, the involvement of AI not only enhances the depth of analysis but also streamlines decision-making processes by automating the assignment of new projects or data, ultimately improving efficiency and productivity in project management workflows. Overall, the incorporation of AI techniques enriched the results by offering sophisticated analysis capabilities and enabling the automation of tasks, ultimately contributing to a more comprehensive understanding of the data and their implications.

8. Implications

The clustering of the aviation project is the process of arranging projects according to shared features or characteristics, which offers several benefits as follows:

Simplified decision-making: When aviation initiatives are clearly categorized, decision-makers can more easily set priorities and decide which projects to take on, how much money to spend, and how to allocate resources.

Better resource allocation: Categorization makes it possible to comprehend and distribute resources more effectively, ensuring that the appropriate resources are provided to the appropriate projects in accordance with their priority and categorization.

Lower risk and improved management: Classification makes it easier to recognize and evaluate the hazards connected to various aviation projects, allowing for proactive risk management techniques to be put into place as needed.

Effective planning and execution: Classification offers an organized framework for aviation project planning and execution, which boosts efficacy and efficiency all the way through the project lifecycle.

Improved benchmarking and performance assessment: With such classification, it will be easier to compare results to other comparable projects and evaluate the performance against standard designs and layouts, which helps pinpoint areas for development.

While the classification of projects has its advantages, there are few challenges that may be encountered in this process, such as the heterogeneity owed to the variations in the projects terms, scope, scale, technology, and, sometimes, cultural matters. The aviation industry is highly complex. Factors such as geopolitical issues, regulatory changes, technological advancements, and market dynamics can significantly impact project clustering efforts. Moreover, effective clustering relies on the availability and quality of data, which may be particularly difficult in this field. Moreover, aviation construction projects are often dynamic and subject to change throughout their lifecycle. Because of its dynamic nature, it can be difficult to keep project classification accurate and relevant over time, especially as new and evolving projects and technologies come into existence.

The study encountered several limitations in acquiring and managing data. Securing the required information on aviation construction projects was hampered by confidentiality restrictions, resulting in less comprehensive datasets. Additionally, identifying the most suitable AI tools for analysis presented further constraints. Furthermore, the manual entry of project attributes proved to be time-consuming. The lack of uniform data formats from many sources makes data integration more difficult and necessitates extra procedures to normalize the data, which raises the risk of mistakes and labor intensity. This intricacy weakens the study's accuracy since erroneous conclusions might be drawn from inconsistent or faulty data, which calls into question the validity of the findings. Furthermore, non-representative or inadequate data may only relate to particular situations rather than larger settings, making it difficult to generalize conclusions due to data-integration issues. Taking care of these problems emphasizes the necessity of having access to extensive and consistent data sources and of using effective techniques, such as sophisticated integration tools and automated cleaning procedures. In order to improve the quality and effect of scientific studies, future research endeavors must prioritize these factors in order to improve the dependability and accuracy of the gathered data.

9. Conclusions

In conclusion, the integration of AI into aviation engineering project management holds great promise due to the demand for innovation in the planning, design, and execution of these projects. There are different types of aviation construction projects that are characterized by special attributes, which are used in a new classification framework. To perform the study, diverse aviation project attributes and characteristics were gathered from the industry and the existing literature. The purpose was to identify the possible similarities and differences within such projects in order to benefit from previous practices that can help identify aviation construction problems ahead of time.

The proposed framework utilizes AI tools such as HC and Neural Networks at different dendrogram levels to form project groups. The classification was then tested using NN to assess the goodness of clustering. The results revealed a remarkable classification capability with a minimal number of classifications errors. The framework showed that there is a great consistency between the clustering resulting from HC and NN. It was found that higher number of clusters yields less distinguishability. Although a low number of clusters provides better insights, it also dilutes the distinction of some projects. The data shows that, with three groups, the error percentage in both the HC and NN is minimal. Better classification provides an accurate and efficient categorization of items, information, and data. In various contexts, better classification can result in improved decision-making, an easier retrieval of information, and an enhanced overall system performance.

For future research, larger sets of data can be used to increase the accuracy of the results, different attributes might be included based on the features of new projects, and various AI/ML tools might also be implemented.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

										Design and Technology			The Level of the Risk																		
Contract Title	Contractual Duration (in Days)	Actual Duration (in Days)	Peak Manpower	Design Duration (in Days)	Project Size	Project Complexity Level	Location	Safety Requirements	The Project Involved Utilizing Building Information Modeling (BIM) for Design and Construction	Level of Technology Integration in the Project	Implementation of Building Management System (BMS)	Technical/Operational Risks	Environmental Risks	Management Related Risks	Requirement of Consultant	Cost/Budget	Sustainability	the Number of Different Engineering Trades/Disciplines Required	Closure Needed or Not	Diversion of Roads	Current Stage	Stakeholders Approval	Back-Up Power Arrangements	Requirement of Long Lead Items	Project Scope Definition	Design from Scratch	Amendments on Existing Design	Level of Interior Design	Survey Requirements	Level of Accessibility	Facility Type
Project #1	360.00	630.00	170	766	1	3	0	3	1	1	1	3	1	2	1	4	3	2	0	1	2	1	1	1	3	0	1	1	1	2	3
Project #2	251.00	524.00	49	509	1	1	1	3	0	1	0	3	3	2	1	2	3	1	0	0	2	0	0	0	2	0	0	2	1	1	3
Project #3	209.00	598.00	51	576	1	2	1	2	0	1	1	3	3	1	1	2	3	2	1	0	2	1	1	0	2	0	0	1	1	1	3
Project #4	378.00	909.00	131	239	1	3	0	3	1	2	1	2	2	3	1	4	3	4	1	1	1	1	1	1	3	0	1	1	1	3	3
Project #5	144.00	144.00	38	0	1	1	0	1	0	3	0	1	1	1	0	2	1	4	1	0	2	0	0	0	3	1	0	3	1	3	3
Project #6	155.00	235.00	7	0	0	1	0	1	0	1	0	1	1	1	0	1	2	3	0	0	2	0	0	0	4	0	1	3	0	2	3
Project #7	263.00	263.00	30	126	1	3	0	1	0	3	1	1	1	1	1	3	3	4	1	0	2	0	0	0	3	1	0	3	1	3	3
Project #8	424.00	530.00	25	39	1	3	0	1	0	2	1	1	1	1	1	3	1	3	1	0	1	0	0	0	3	1	0	1	1	3	2
Project #9	659.00	671.00	17	1030	1	2	0	3	0	2	1	3	2	1	1	2	3	2	0	0	2	1	1	1	1	0	0	1	1	2	0
Project #10	786.00	606.00	4	86	1	3	1	1	0	2	0	2	1	1	1	2	3	2	1	0	2	0	0	1	1	0	1	1	1	1	5
Project #11	1045.00	1395.00	50	1089	0	3	0	3	0	3	1	3	2	2	1	3	3	2	0	0	1	1	1	0	1	0	1	1	1	3	4
Project #12	560.00	560.00	47	805	0	2	0	1	1	2	1	3	1	2	1	2	3	4	0	0	2	0	0	0	1	0	1	1	1	3	1
Project #13	209.00	209.00	25	326	0	1	0	2	0	2	0	1	1	1	1	1	3	4	1	1	1	0	0	0	3	0	1	3	0	1	2
Project #14	419.00	1193.00	20	519	1	2	0	3	0	1	1	3	1	2	1	3	3	1	0	0	2	1	1	1	3	0	1	1	1	3	0
Project #15	397.00	1406.00	26	142	1	2	0	3	0	1	1	3	1	2	1	4	3	2	0	0	1	1	1	1	1	0	1	1	1	2	0
Project #16	299.00	645.00	14	103	1	2	0	2	0	1	1	2	1	1	1	2	3	3	1	0	2	1	0	0	1	0	0	1	1	2	0
Project #17	283.00	518.00	50	825	1	3	1	1	0	2	1	2	1	2	1	2	2	3	1	1	2	1	1	0	1	0	0	1	1	3	0
Project #18	299.00	517.00	18	514	1	2	0	3	0	2	1	3	2	3	1	3	3	2	1	1	1	0	0	0	3	0	0	1	0	3	0
Project #19	879.00	879.00	82	1000	1	2	0	3	0	2	1	3	1	2	1	4	3	2	0	0	1	1	1	1	1	0	1	1	1	3	0
Project #20	885.00	852.00	9	401	1	1	1	2	0	1	0	2	1	1	1	2	3	2	1	0	1	0	0	1	1	0	0	1	1	2	5

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