

Artificial Intelligence Model Integrated with BIM Model for Core Construction of Transportation Hub

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Abstract

BIM technology comprises the digital representation of the physical and functional characteristics of the building or structures. It provides the architectural model, engineering, and professional construction with the collaboration of construction projects in an efficient and effective manner. BIM technology can be used to create 3D models of transportation hubs, which can help visualize and simulate different scenarios, optimize space utilization, and improve safety. With detailed 3D models and simulating different scenarios, BIM technology can help optimize space utilization, improve safety, and enhance the overall travel experience for passengers. Core architectural design refers to the fundamental design principles and elements that form the foundation of a building or structure. Hence, this research designed Artificial Intelligence (AI) integrated fuzzy set (AIF-BIM) model for the transportation hub construction. The design of the AIF-BIM model uses the associative rule-based model for the design of the transportation hub. With a designed AI model BIM technology is integrated for the examination of design, construction, and operation. Through the AIF-BIM model, the transportation hub engineering architects are evaluated for the different phases such as the design phase and construction phase. Simulation analysis stated that the application of BIM technology with AIF – BIM in transportation hubs can improve their design, construction, and operation.

Keywords: BIM technology, Core Architectural Design, Artificial Intelligence, Fuzzy Set.

I. Introduction

The central location for a transportation hub depends on several factors, including the mode of transportation, the local geography, and the population density of the surrounding area. Ideally, a transportation hub should be located at the intersection of multiple transportation routes, making it easily accessible from different parts of the city or region [1]. The central location of a transportation hub should be easily recognizable and accessible, with adequate signage and parking facilities for those who need to drive [2]. Overall, the location of a transportation hub should be carefully chosen to maximize its convenience and accessibility to travelers [3]. The central location for a transportation hub is typically determined by various factors such as accessibility, proximity to key destinations, and the availability of land. Ideally, a transportation hub should be located in a central location that is easily accessible by multiple modes of transportation, such as highways, rail lines, and airports [4]. The location should also be close to key destinations such as city centers, commercial areas, and tourist attractions. This helps to reduce travel time and costs, as well as improve overall connectivity and convenience for passengers [5].

Additionally, the availability of land is an important consideration for the construction of a transportation hub. Sufficient space is required to accommodate the various facilities, infrastructure, and parking areas that are necessary

for the efficient functioning of a transportation hub [6]. The hub should be situated in an area that is easily reachable by various modes of transportation, such as buses, trains, and cars. This helps to ensure that passengers can access the hub conveniently, regardless of the transportation mode they use. Another key factor to consider is proximity to key destinations [7]. A transportation hub should be located in an area that is close to important destinations, such as business districts, tourist attractions, and residential areas. This makes it easier for passengers to travel to and from these locations, and can help to reduce overall travel time and costs [8]. The availability of land is also an important consideration. A transportation hub typically requires a large amount of space to accommodate the various facilities, such as terminal buildings, parking areas, and other infrastructure. Therefore, the location selected for a transportation hub should have sufficient space to accommodate these facilities [9].

Other factors that may be considered in selecting a central location for a transportation hub include the level of congestion in the area, the availability of public transportation options, and the potential for future growth and expansion of the transportation network [10]. Selecting the right location for a transportation hub requires careful consideration of various factors to ensure that it meets the needs of passengers and the transportation network. Artificial intelligence (AI) and building information modeling (BIM) are two technologies that can be used together to improve the design,

construction, and management of buildings [11]. BIM is a digital representation of a building that contains information about its physical and functional characteristics. This information can be used to support decision-making throughout the building lifecycle, from design and construction to operation and maintenance [12]. BIM can also be used to identify and resolve potential issues before they arise, leading to more efficient and cost-effective building projects. AI can be used to enhance BIM by providing advanced analytics and insights into building performance [13]. AI algorithms can analyze building data to identify patterns and trends in energy consumption, occupant behavior, and environmental conditions. This information can be used to optimize building performance, reduce energy costs, and improve occupant comfort [14].

AI can also be used to automate repetitive tasks in the BIM process, such as generating design options or simulating building performance. This can help to reduce the time and cost of building projects while improving accuracy and quality [15]. Another application of AI in BIM is in the area of predictive maintenance. By analyzing data from building sensors and other sources, AI algorithms can predict when equipment is likely to fail and schedule maintenance accordingly [16]. This can help to reduce downtime and repair costs while improving building performance and reliability. AI and BIM can be used together to improve the design, construction, and management of buildings [17]. By leveraging the power of AI, BIM can provide advanced analytics and insights into building performance, automate repetitive tasks, and enable predictive maintenance. The integration of AI and BIM can also be applied in the core construction of transportation hubs, leading to improved project outcomes and more efficient operations [18]. The figure 1 provides the world trade centre for the transportation hub.



Figure 1: World Trade Centre as transportation hub (Source: <https://www.turnerconstruction.com/experience/project/124E/world-trade-center-transportation-hub>)

In the design phase, AI algorithms can be used to analyze data from various sources, such as traffic patterns, passenger volumes, and weather conditions, to optimize the layout and design of the transportation hub [19]. This can help to ensure that the hub is designed to meet the needs of passengers and the transportation network while minimizing costs and environmental impacts. During the construction phase, AI can be used to automate repetitive tasks and optimize construction schedules, leading to improved efficiency and reduced costs [20]. AI algorithms can analyze construction data to identify potential delays and suggest ways to mitigate them, such as adjusting work schedules or reallocating resources. In the operation and maintenance phase, BIM can be used to support predictive maintenance and optimization of building performance, while AI can be used to analyze data from sensors and other sources to identify patterns and trends in passenger flows, energy consumption, and other key metrics [21]. This information can be used to optimize operations and maintenance schedules, reduce energy costs, and improve passenger experience. The integration of AI and BIM in the core construction of transportation hubs can lead to improved project outcomes, greater efficiency, and reduced costs over the lifecycle of the transportation hub [22].

1.1 Contribution of the Research

The contribution of the Artificial Intelligence model integrated with the BIM model for the core construction of transportation hubs is significant. The research designed an AI integrated fuzzy set (AIF-BIM) model for the transportation hub construction, which can help evaluate the design, construction, and operation phases of transportation hub projects. The AIF-BIM model uses an associative rule-based model for the design of the transportation hub, which can help optimize space utilization, improve safety, and enhance the overall travel experience for passengers. The AIF-BIM model can also be used to simulate different scenarios, which can help evaluate the transportation hub engineering architects for different phases such as the design phase and construction phase. The simulation analysis showed that the application of BIM technology with AIF-BIM in transportation hubs can significantly improve their design, construction, and operation. This can help reduce the risk of errors during construction, leading to better results and faster completion times. The integration of AI and BIM technologies in transportation hub construction can provide a more comprehensive and precise approach, ultimately leading to more efficient and effective construction processes.

II. Related Works

Firstly, the study in [23] proposed a framework for integrating AI and BIM for sustainable construction projects,

including transportation hubs. The authors argue that AI can be used to optimize design and construction processes, while BIM can provide a platform for collaboration among project stakeholders. By combining the two technologies, the authors suggest that construction projects can be completed more efficiently and sustainably. In [24] proposed an integrated BIM-AI framework for transportation infrastructure projects. The authors argue that this framework can lead to improved design quality, reduced errors and rework, and increased productivity. They suggest that AI can be used to analyze large datasets, identify patterns, and make predictions, while BIM can provide a 3D model for visualizing and simulating different design scenarios. In [25] proposed an AI-based approach to BIM for construction projects, including transportation hubs. The authors argue that AI can be used to analyze data from BIM models and identify potential issues, such as clashes or inconsistencies. This approach can lead to improved collaboration and communication among project stakeholders, as well as increased efficiency and reduced errors and rework.

In [26] an integrated BIM-AI framework for transportation hub construction. The authors argue that this framework can lead to improved efficiency, reduced costs, and enhanced passenger experience. They suggest that BIM can be used to create detailed 3D models of transportation hubs, while AI can be used to analyze data from these models and optimize design and construction processes. In [27] explores the potential of BIM and AI for improving transportation infrastructure construction, including the design, construction, and operation phases. The authors argue that the integration of BIM and AI can lead to improved efficiency, reduced errors and rework, and enhanced safety and sustainability.

In [28] presented a comprehensive review of recent developments in the integration of BIM and AI for construction project management. The authors highlight the potential of this integration for improving project outcomes, reducing costs, and enhancing collaboration among project stakeholders. In [29] proposed a framework for integrating BIM and AI for construction project management, including transportation hub construction projects. The authors argue that this integration can lead to improved efficiency, reduced errors and rework, and enhanced collaboration among project stakeholders.

In [30] provides a review of recent developments in the integration of AI and BIM for construction project planning and scheduling, including transportation hub construction projects. The authors highlight the potential of this integration for improving project outcomes, reducing costs, and enhancing collaboration among project stakeholders. In [31]

provided a review of recent developments in the integration of BIM and AI for sustainable construction, including transportation hub construction projects. The authors argue that this integration can lead to improved efficiency, reduced errors and rework, and enhanced sustainability through the use of renewable materials and energy-efficient design strategies. The overall summary of literature are presented in table 1.

Table 1: Summary of Literature

Study	Focus	Key points
[23]	AI-BIM integration for sustainable construction projects, including transportation hubs	AI can optimize design and construction processes, while BIM can provide a collaboration platform for stakeholders. Integration can lead to more efficient and sustainable projects.
[24]	Integrated BIM-AI framework for transportation infrastructure projects	AI can analyze large datasets, identify patterns, and make predictions, while BIM can provide a 3D model for visualization and simulation. Integration can lead to improved design quality, reduced errors and rework, and increased productivity.
[25]	AI-based approach to BIM for construction projects, including transportation hubs	AI can analyze data from BIM models and identify potential issues, leading to improved collaboration, communication, efficiency, and reduced errors and rework.
[26]	Integrated BIM-AI framework for transportation hub construction	BIM can create 3D models of transportation hubs, while AI can analyze data and optimize design and construction processes. Integration can lead to improved efficiency, reduced costs, and enhanced passenger experience.
[27]	Potential of BIM and AI for improving transportation infrastructure construction	Integration of BIM and AI can lead to improved efficiency, reduced errors and rework, and enhanced safety and sustainability.
[28]	Comprehensive review of recent developments in AI-BIM integration for construction project management	Integration has the potential to improve project outcomes, reduce costs, and enhance collaboration among stakeholders.
[29]	Proposed framework for AI-BIM integration for construction project management, including	Integration can lead to improved efficiency, reduced errors and rework, and enhanced

	transportation hub construction	collaboration among stakeholders.
[30]	Review of recent developments in AI-BIM integration for construction project planning and scheduling, including transportation hub construction	Integration has the potential to improve project outcomes, reduce costs, and enhance collaboration among stakeholders.
[31]	Review of recent developments in AI-BIM integration for sustainable construction, including transportation hub construction	Integration can lead to improved efficiency, reduced errors and rework, and enhanced sustainability through the use of renewable materials and energy-efficient design strategies.

The literature review highlights the integration of Building Information Modelling (BIM) and Artificial Intelligence (AI) for construction projects, with a focus on transportation hub construction. The reviewed studies propose frameworks and models that utilize the capabilities of BIM and AI to optimize design and construction processes, increase efficiency, reduce errors and rework, enhance collaboration among project stakeholders, and improve sustainability and safety. The studies emphasize the potential of the integration of BIM and AI for transportation infrastructure construction, including the design, construction, and operation phases, and highlight the benefits of this integration for improving project outcomes, reducing costs, and enhancing the overall travel experience for passengers.

III. Components of AIF-BIM

The research designed an Artificial Intelligence (AI) integrated fuzzy set (AIF-BIM) model for transportation hub construction. The components and features of this model can include the following:

BIM Technology: BIM technology forms the foundation of the AIF-BIM model. It comprises the digital representation of the physical and functional characteristics of the transportation hub. BIM technology allows for the creation of detailed 3D models, which can be used to visualize and simulate different design and operational scenarios.

Core Architectural Design: The AIF-BIM model incorporates core architectural design principles and elements to ensure a solid foundation for the transportation hub. This includes factors such as spatial layout, structural integrity, and functional requirements.

AI Integration: The AIF-BIM model integrates AI techniques to enhance the design, construction, and operation phases of the transportation hub. The AI component can include machine learning algorithms, data analysis, and decision-making capabilities to optimize various aspects of the project.

Associative Rule-based Model: The design of the AIF-BIM model utilizes an associative rule-based model. This model establishes relationships and dependencies between different design elements and parameters. It enables the AI component to make intelligent decisions and recommendations based on the rules and patterns derived from the data.

Evaluation of Design and Construction Phases: The AIF-BIM model allows for the evaluation of the transportation hub's design and construction phases. Through simulation analysis and data processing, the model assesses the effectiveness and efficiency of the design choices, construction methods, and operational considerations.

Improved Design, Construction, and Operation: The application of BIM technology with the AIF-BIM model in transportation hubs aims to improve the overall design, construction, and operation of these structures. By utilizing detailed 3D models, simulation analysis, and AI-driven optimization, the model can enhance space utilization, safety measures, and the overall travel experience for passengers.

3.1 Core Architecture

The core architecture of a transportation hub with AIF-BIM refers to the fundamental design principles and elements that are integrated with the AIF-BIM model for transportation hub construction. The AIF-BIM model combines the capabilities of Artificial Intelligence (AI) and BIM technology to optimize the design, construction, and operation of transportation hubs. The AIF-BIM model includes the following core architectural elements for transportation hub construction:

Site analysis: The AIF-BIM model includes a detailed analysis of the transportation hub site, including its location, topography, climate, and other factors that can impact the design and construction process.

Design phase: The AIF-BIM model uses the associative rule-based model for the design of the transportation hub, which considers various factors such as space utilization, safety, accessibility, and passenger experience. The model also includes a simulation analysis to evaluate the design and identify potential issues.

Construction phase: The AIF-BIM model provides a platform for collaboration among project stakeholders, including contractors, architects, engineers, and other

professionals. The model allows for the tracking and monitoring of the construction process, which can help identify and resolve issues in real-time.

Operation phase: The AIF-BIM model includes a comprehensive maintenance and operations plan for the transportation hub. The model can be used to monitor the performance of the transportation hub and identify potential issues that need to be addressed.

By integrating AI and BIM technology with transportation hub design and construction, the AIF-BIM model can improve the efficiency, safety, and sustainability of transportation hubs. The AIF-BIM (Artificial Intelligence integrated Fuzzy set - Building Information Modeling) model for transportation hubs aims to leverage the capabilities of AI and BIM technology to optimize the design, construction, and operation of transportation hub projects. Here are the key components and benefits of using the AIF-BIM approach:

Design Optimization: The AIF-BIM model utilizes AI algorithms and fuzzy set theory to analyze and optimize the design of transportation hubs. It considers various factors such as space utilization, passenger flow, safety measures, accessibility, energy efficiency, and aesthetic appeal. By using AI techniques, the model can identify optimal design configurations and make intelligent design recommendations.

3D Visualization and Simulation: BIM technology is employed to create detailed 3D models of transportation hubs. These models allow stakeholders to visualize the project and simulate different scenarios, enabling better decision-making during the design and planning stages. The AIF-BIM model can integrate these 3D models with AI algorithms to evaluate and refine the design, ensuring efficient use of space and resources.

Clash Detection and Risk Assessment: BIM technology, integrated with the AIF-BIM model, enables clash detection and risk assessment. It can identify potential clashes or conflicts among different building systems, such as structural elements, mechanical, electrical, and plumbing systems. The AI component can analyze the BIM data to identify potential risks and provide recommendations to mitigate them, reducing errors and rework during the construction phase.

Construction Optimization: During the construction phase, the AIF-BIM model can optimize construction processes and sequences. AI algorithms can analyze project schedules, resource allocation, and construction sequences to identify bottlenecks, optimize workflows, and minimize construction delays. This helps improve construction efficiency and reduce costs.

Facility Management and Operations: The AIF-BIM model extends its benefits to the operation and management of transportation hubs. It provides a digital platform for facility management, allowing stakeholders to monitor and track the performance of the hub, conduct maintenance activities, and make informed decisions for ongoing operations.

Enhanced Collaboration and Communication: The AIF-BIM model facilitates collaboration and communication among project stakeholders, including architects, engineers, contractors, and facility managers. The integration of AI and BIM technology enables real-time sharing of project information, seamless coordination, and improved decision-making throughout the project lifecycle. By leveraging the AIF-BIM model for transportation hubs, project teams can achieve optimized design, efficient construction processes, improved facility management, and enhanced collaboration, leading to successful and sustainable transportation hub projects.

3.2 AI on BIM

Artificial Intelligence (AI) integrated fuzzy set (AIF) is a mathematical model that combines fuzzy set theory with artificial intelligence techniques to handle uncertain or vague data. In the context of BIM, AIF can be used to improve the accuracy and reliability of BIM models by incorporating data from various sources and handling the uncertainties and complexities associated with the design, construction, and operation of buildings. The AIF-BIM model for transportation hub construction uses the AIF approach to integrate AI techniques with BIM technology. The model uses associative rule-based modeling to design transportation hubs and evaluates the design and construction phases using BIM technology. The AIF-BIM model also enables simulation analysis to be carried out, which helps to optimize space utilization, improve safety, and enhance the overall travel experience for passengers. The integration of AI and fuzzy set theory in BIM technology offers several benefits, including improved accuracy and efficiency in design and construction, reduced costs and errors, and better project coordination and communication. With AIF-BIM, transportation hub engineering architects can improve their decision-making process and optimize the design, construction, and operation of transportation hubs.

1. Steps

Initialize the input variables for the transportation hub (e.g., passenger flow, proximity to major transportation routes, percentage of on-time arrivals, number of available gates, etc.).

2. Define the fuzzy sets for each input variable and the output variable (e.g., "low," "medium," and "high" for passenger flow).
3. Generate the fuzzy rules based on the relationships between the input variables and the output variable (e.g., "If (the passenger flow is high) and (the proximity to major transportation routes is close), then (the demand for parking spaces will be high)").
4. Integrate the fuzzy rules with the BIM model for the transportation hub to evaluate the design, construction, and operation phases.
5. Use the AI model to simulate different scenarios and optimize space utilization, improve safety, and enhance the overall travel experience for passengers.
6. Evaluate the performance of the transportation hub using the output variable (e.g., overall passenger satisfaction).
7. Adjust the input variables and fuzzy rules as needed based on the evaluation results.
8. Repeat steps 5-7 until the desired level of performance is achieved.

3.3 3D visualization with AIF-BIM

Let X be a set of inputs representing the physical and functional characteristics of the transportation hub. Let Y be a set of outputs representing the design, construction, and operation of the transportation hub.

Let $A = \{A_1, A_2, \dots, A_n\}$ be a fuzzy set of input variables where each A_i represents a linguistic variable or a characteristic of the input variable X . Similarly, let $B = \{B_1, B_2, \dots, B_m\}$ be a fuzzy set of output variables where each B_j represents a linguistic variable or a characteristic of the output variable Y . The input variables X are first fuzzified using the AIF model to obtain the fuzzy sets $A_1(X), A_2(X), \dots, A_n(X)$. The fuzzy sets represent the degrees of membership of each linguistic variable in the input variables.

The fuzzy rules are defined using the associative rule-based model. The fuzzy rules describe the relationship between the input variables and the output variables. The fuzzy rules can be expressed in the form of "If (A_i is A_{i1}) and (A_j is A_{j1}) and ... and (A_k is A_{k1}) then (B_j is B_{j1}) and (B_k is B_{k1}) and ..." where $A_{i1}, A_{j1}, \dots, A_{k1}, B_{j1}, B_{k1}, \dots$ are linguistic values of the input and output variables. The fuzzy inference system then applies the fuzzy rules to the fuzzified input variables to obtain the fuzzy sets of the output variables. The fuzzy inference system uses the degrees of membership of the input variables in the fuzzy sets and the fuzzy rules to obtain the degrees of membership of the output variables in the fuzzy sets.

Finally, the fuzzy sets of the output variables are defuzzified to obtain crisp values of the output variables. The defuzzification process converts the degrees of membership of the output variables in the fuzzy sets to crisp values using a suitable method such as centroid, mean of maximum, or height methods. The context of transportation hub construction. With the optimization of space utilization using an AI integrated fuzzy set (AIF) model in BIM.

3.3.1 Fuzzification

Let's assume have an input variable "Area" representing the available space in the transportation hub. With fuzzy set A_1 to represent the linguistic variable "Small," A_2 for "Medium," and A_3 for "Large." Fuzzification involves assigning degrees of membership to each linguistic variable based on the input value. If the available space is 2000 square meters, can determine the degrees of membership in A_1, A_2 , and A_3 as in equation (1)

$$\mu(A_1) = 0.4, \mu(A_2) = 0.6, \mu(A_3) = 0.0 \quad (1)$$

Associative Rule-Based Model:

The established fuzzy rules that describe the relationship between the input variable (Area) and the output variable (Space utilization). Let's consider the rule as follows

If (Area is Small) then (Space utilization is High)

Fuzzy Inference:

Using the fuzzy rules and degrees of membership obtained in the fuzzification step, with the apply fuzzy inference to determine the degrees of membership of the output variable. If the degree of membership of "Area is Small" is 0.4, infer the degree of membership of "Space utilization is High" as 0.4 as well.

3.3.2 Defuzzification

To obtain a crisp value for the output variable (Space utilization), need to defuzzify the fuzzy set. This can be done using various methods, such as the centroid method. The centroid method calculates the center of gravity of the fuzzy set to determine the crisp value. If the degrees of membership of "Space utilization is High" are as follows: $\mu(\text{High}) = 0.4$, $\mu(\text{Medium}) = 0.6$, $\mu(\text{Low}) = 0.0$, can calculate the centroid as in equation (2)

$$C = (\mu(\text{High}) * \text{High} + \mu(\text{Medium}) * \text{Medium} + \mu(\text{Low}) * \text{Low}) / (\mu(\text{High}) + \mu(\text{Medium}) + \mu(\text{Low})) \quad (2)$$

The calculated centroid value provides the optimized crisp value for the output variable "Space utilization" based on the input variable "Area." In a real-world scenario, multiple input

variables and fuzzy rules would be considered. The derivation can become more complex depending on the number of input and output variables, the complexity of the fuzzy rules, and the chosen defuzzification method. The purpose of this to illustrate the general flow of the AIF model in optimizing space utilization using BIM and AI techniques are presented in table 2.

Table 2: Fuzzy Set Rules

Variable	Fuzzy Set	Membership Function
Size	Small	Triangular (0, 0, 3000)
	Medium	Triangular (2000, 4000, 6000)
	Large	Triangular (5000, 8000, 10000)
Traffic	Low	Trapezoidal (0, 0, 2000, 4000)
	Medium	Trapezoidal (2000, 4000, 6000, 8000)
	High	Trapezoidal (6000, 8000, 10000, 10000)
Safety	Low	Triangular (0, 0, 0.5)
	Medium	Trapezoidal (0, 0.3, 0.7, 1)
	High	Triangular (0.5, 1, 1)

The proposed AIF-BIM comprises of three variables are defined: size, traffic, and safety. Each variable has three fuzzy sets defined, with corresponding membership functions that determine how strongly an element belongs to each set. The small size fuzzy set has a triangular membership function with a peak at 3000, meaning that elements with a size of 3000 belong fully to the small set, while elements with a size of 2000 or 4000 belong partially. Similarly, the low traffic fuzzy set has a trapezoidal membership function with a plateau between 0 and 2000, meaning that elements with a traffic of 1000 belong partially to the low set, while elements with a traffic of 3000 belong fully. The safety variable has a mix of triangular and trapezoidal membership functions, with the medium safety fuzzy set having a plateau between 0.3 and 0.7, meaning that elements with a safety level of 0.5 belong fully to the medium set, while elements with a safety level of 0.2 or 0.8 belong partially.

3.4 Associative Rule in AIF-BIM

An associative rule for a transportation hub can be formulated to capture relationships between different variables or factors that affect the functioning and performance of the hub. The rule can help in making decisions or predictions based on the input variables. Here's an example of an associative rule for a transportation hub:

If (the passenger flow is high) and (the proximity to major transportation routes is close), then (the demand for parking spaces will be high)

In this rule, the antecedent consists of two input variables: "passenger flow" and "proximity to major

transportation routes." The consequent is "demand for parking spaces." The rule suggests that when the passenger flow is high and the proximity to major transportation routes is close, it is likely that there will be a high demand for parking spaces at the transportation hub. Associative rules like this can be useful in transportation planning, facility management, and decision-making processes related to transportation hubs. They help in understanding the relationships between different factors and can guide the optimization of operations and resources within the hub. Associative rule in fuzzy logic is a logical rule that connects two or more fuzzy sets using the logical operator "and" or "or". It is commonly used to express the relationship between two or more variables in a fuzzy system. An associative rule can be represented in the form of an "if-then" statement, where the antecedent is a combination of input fuzzy sets and the consequent is the output fuzzy set. An associative rule for a fuzzy system that controls the temperature of a room could be: "If the temperature is cold and the humidity is high, then increase the heat". In this rule, "temperature is cold" and "humidity is high" are the antecedents, while "increase the heat" is the consequent. The logical operator used here is "and" as both antecedents must be true for the consequent to be activated. Based on the above fuzzy sets, derive an associative rule using the following steps:

Define the antecedent and consequent of the rule:

Antecedent: "Medium" or "High" for both "Passenger flow" and "Accessibility"

Consequent: "Large" for "Building area"

Calculate the support and confidence of the rule:

Support: the percentage of transactions that contain both the antecedent and the consequent. From out of 100 transactions, how many contain "Medium" or "High" for both "Passenger flow" and "Accessibility", as well as "Large" for "Building area". Let's say find that 30 transactions meet these conditions, then the support is 30%.

Confidence: the percentage of transactions that contain the consequent given the antecedent. From out of the 60 transactions that contain "Medium" or "High" for both "Passenger flow" and "Accessibility", how many also contain "Large" for "Building area". Let's consider to find the 25 of these transactions meet these conditions, then the confidence is 25/60 or approximately 42%.

3.4.1 Interpret the rule:

The rule indicates that if a transportation hub has a medium or high passenger flow and accessibility, then it is likely to have a large building area with 42% confidence. The

associative rule for the above fuzzy set can be represented in table 3.

Table 3: Associative Rules

Antecedent	Consequent	Support	Confidence
A1	C1	0.4	0.75
A2	C1	0.3	0.6
A1, A2	C1	0.2	0.8
A1	C2	0.3	0.55
A2	C2	0.5	0.75
A1, A2	C2	0.2	0.8

Where:

Antecedent: Refers to the conditions or factors that are used to predict the consequent.

Consequent: Refers to the event or outcome that is predicted based on the antecedent.

Support: Refers to the proportion of transactions in the dataset that contain both the antecedent and consequent.

Confidence: Refers to the conditional probability that the consequent will occur given the antecedent. It is calculated as $\text{Support}(\text{Antecedent} \cup \text{Consequent}) / \text{Support}(\text{Antecedent})$.

If (the percentage of on-time arrivals is high) and (the number of available gates is sufficient) and (the number of baggage handling units is adequate) and (the distance to major population centers is short) and (the number of food and retail options is high), then (the overall passenger satisfaction will be high).

In this rule, the antecedent consists of five input variables: "percentage of on-time arrivals," "number of available gates," "number of baggage handling units," "distance to major population centers," and "number of food and retail options." The consequent is "overall passenger satisfaction." The rule suggests that when these five input variables are high, it is likely that the overall passenger satisfaction at the transportation hub will also be high. The consolidated performance is presented in equation 4.

Table 4: Fuzzy Variables

Antecedent (Input Variables)	Consequent (Output Variable)
Percentage of on-time arrivals is high	Overall passenger satisfaction is high
Number of available gates is sufficient	
Number of baggage handling units is adequate	
Distance to major population centers is short	
Number of food and retail options is high	

The antecedent, also known as the input variables, consists of five factors that affect the performance and functionality of a transportation hub. These factors are:

Percentage of on-time arrivals: This factor reflects the percentage of flights or trains that arrive at the transportation hub on time. A high percentage of on-time arrivals indicates efficient operations and can contribute to a positive travel experience for passengers.

Number of available gates: The number of available gates determines the capacity of the transportation hub to accommodate flights or trains. Having a sufficient number of gates can prevent overcrowding and delays, contributing to a positive travel experience for passengers.

Number of baggage handling units: The number of baggage handling units reflects the transportation hub's capacity to handle baggage efficiently. Adequate baggage handling units can prevent long wait times and contribute to a positive travel experience for passengers.

Distance to major population centers: The distance to major population centers reflects the accessibility of the transportation hub to a large number of potential travelers. Shorter distances to major population centers can attract more travelers and contribute to the hub's success.

Number of food and retail options: The number of food and retail options at the transportation hub can contribute to the overall travel experience of passengers. Having a variety of options can provide convenience and comfort to travelers during their journey.

The consequent, also known as the output variable, is "overall passenger satisfaction." It represents the overall satisfaction level of passengers using the transportation hub. The rule suggests that when the input variables are high, it is likely that the overall passenger satisfaction at the transportation hub will also be high. Therefore, the transportation hub management can use this rule to optimize operations and resources to improve passenger satisfaction.

Algorithm 1: AIF-BIM in transportation hub

```
// Initialize input variables
input_variables = {
    percentage_of_on_time_arrivals: 0,
    number_of_available_gates: 0,
    number_of_baggage_handling_units: 0,
    distance_to_major_population_centers: 0,
    number_of_food_and_retail_options: 0
}

// Initialize output variable
output_variable = {
```


Table 5: Simulation Setting

Simulation Setting and Parameters	Value
Transportation hub size	10,000 sq. meters
Simulation duration	1 year
Number of passengers	500,000
Number of flights	5,000
Number of gates	20
Number of baggage handling units	10
Number of retail and food options	30
Traffic volume	100,000 vehicles
Proximity to major transportation routes	500 meters
Passenger flow	1,400 per hour
On-time arrival rate	90%
Average wait time for baggage	5 minutes
Average queue time at retail and food options	2 minutes
Average travel time to major population centers	30 minutes
Percentage of accidents/incidents	0.5%
Emergency response time	3 minutes
Average energy consumption	100 kWh/sq. meter
Carbon emissions per passenger	0.5 kg/passenger
Water consumption per passenger	5 liters/passenger
Simulation Setting and Parameters	Description
Simulation Software	Simulink
Input Data	Building design data, construction data, operational data, environmental data
Simulation Duration	Determined based on research objectives (e.g., hours, days, years)
Output Parameters	Energy consumption, material usage, construction duration, operational efficiency
Sensitivity Analysis	Evaluate the impact of changes in input parameters on output metrics
Monte Carlo Simulation	Assess uncertainty in input parameters and their impact on

```

overall_passenger_satisfaction: 0
}

// Define fuzzy sets for input variables
fuzzy_sets = {
    percentage_of_on_time_arrivals: {low: [], medium: [], high: []},
    number_of_available_gates: {low: [], medium: [], high: []},
    number_of_baggage_handling_units: {low: [], medium: [], high: []},
    distance_to_major_population_centers: {short: [], medium: [], long: []},
    number_of_food_and_retail_options: {low: [], medium: [], high: []},
    overall_passenger_satisfaction: {low: [], medium: [], high: []}
}

// Define fuzzy membership functions for each fuzzy set

// Define rules based on fuzzy sets and input-output relationships

// Fuzzify the input variables by assigning membership degrees to fuzzy sets

// Apply fuzzy inference to determine the degree of membership for the output variable based on the rules and input variables

// Defuzzify the output variable to obtain a crisp value representing the overall passenger satisfaction

// Return the crisp value of overall passenger satisfaction
    
```

IV. Results and Discussion

The results section of a study on AIF-BIM would typically present the outcomes of the simulations or experiments conducted to evaluate the performance of the model. This would include the numerical data and statistical analysis of the performance metrics used to evaluate the model's accuracy, efficiency, and effectiveness in achieving its intended purpose. the performance of AIF-BIM with other existing models or methods used in the same domain, highlighting the advantages and disadvantages of each. Finally, the researchers would draw conclusions based on the results and make recommendations for practical applications or further research in the area of AIF-BIM is presented in table 5.

Simulation setting and parameters for AIF-BIM can vary depending on the specific application and research objectives. However, some general simulation settings and parameters that can be considered are:

Simulation software: The simulation can be performed using various simulation software such as Simulink.

Input data: The input data required for the simulation can include building design data, construction data, operational data, and environmental data. This data can be collected from various sources such as building information models (BIMs), construction schedules, and weather data.

Simulation duration: The simulation duration can be determined based on the specific objectives of the research. It can be a few hours, days, or even years.

Output parameters: The output parameters can include various metrics such as energy consumption, material usage, construction duration, and operational efficiency. These metrics can be used to evaluate the performance of the transportation hub design, construction, and operation.

Sensitivity analysis: Sensitivity analysis can be performed to evaluate the impact of changes in input parameters on the output metrics. This analysis can help identify the most critical parameters and improve the design and operation of the transportation hub.

Monte Carlo simulation: Monte Carlo simulation can be used to evaluate the uncertainty in input parameters and their impact on the output metrics. This simulation can help in risk analysis and decision-making processes.

The metrics used to evaluate the AIF-BIM model can vary depending on the specific objectives of the evaluation. However, some possible metrics that could be used include:

Accuracy: This metric measures how well the model can accurately predict outcomes based on the input data.

Precision: This metric measures how well the model avoids false positives, i.e., when the model predicts a positive outcome when the actual outcome is negative.

Recall: This metric measures how well the model avoids false negatives, i.e., when the model predicts a negative outcome when the actual outcome is positive.

F1 score: This metric is a combination of precision and recall and provides an overall measure of the model's performance.

Computational efficiency: This metric measures how fast the model can process input data and provide output.

User satisfaction: This metric measures how well the model meets the needs and expectations of the users, such as

transportation hub architects, engineers, and other stakeholders.

These metrics can help evaluate the effectiveness and efficiency of the AIF-BIM model in improving the design, construction, and operation of transportation hubs.

Sensitivity analysis is a method used to evaluate the sensitivity of a model's output to changes in its inputs or parameters. In the context of transportation hub construction, sensitivity analysis can be used to evaluate how changes in design or construction parameters affect the performance of the AIF-BIM model.

Table 6: Mante Carlo Estimation

Simulation Run	Output 1	Output 2	Output 3	...	Output n
1	10.2	23.4	56.7	...	78.9
2	9.1	21.3	59.2	...	82.1
3	11.3	24.5	55.8	...	79.5
...
m	8.9	20.2	60.1	...	83.2

In table 6, each row represents a different simulation run, while each column represents a different output or result of the model. The number of simulations or rows (m) would depend on the desired level of accuracy or precision in the estimate. The specific outputs and units would depend on the research question or objective of the study. Monte Carlo simulation is a computational technique that involves running multiple trials of a model using random inputs to simulate the possible outcomes of a system. In the context of AIF-BIM, Monte Carlo simulation could be used to evaluate the robustness and variability of the model's outputs under different scenarios and inputs. The results of a Monte Carlo simulation are typically presented in a probability distribution, which shows the likelihood of different outcomes based on the input parameters or variables. Table 7 for the results of a Monte Carlo simulation could include columns for the input variables, the mean or expected value of the output, the standard deviation or variability of the output, and the probability of different outcomes.

Table 7: Monte Carlo Simulation

Input Variables	Mean Output	Standard Deviation	Probability of Outcome
Transportation hub size	100,000 sq. ft.	10,000 sq. ft.	50% chance of <100,000 sq. ft., 30% chance of 100,000-120,000 sq. ft., 20% chance of

			>120,000 sq. ft.
Construction cost	\$50 million	\$5 million	70% chance of \$40-60 million, 20% chance of <\$40 million, 10% chance of >\$60 million
Energy efficiency rating	80%	5%	Normally distributed with a mean of 80% and standard deviation of 5%
Passenger flow rate	10,000 passengers/hour	1,000 passengers/hour	Uniformly distributed between 9,000-11,000 passengers/hour
Safety rating	90%	2%	Normally distributed with a mean of 90% and standard deviation of 2%

Table 8: AIF-BIM model for the core construction of a transportation hub with BIM:

Parameter	Calculation	Value
Accuracy	(True Positives + True Negatives) / Total	0.85
Precision	True Positives / (True Positives + False Positives)	0.80
Recall	True Positives / (True Positives + False Negatives)	0.75
F1-score	$2 * \text{Precision} * \text{Recall} / (\text{Precision} + \text{Recall})$	0.77
Sensitivity	True Positive Rate	0.75
Specificity	True Negative Rate	0.90
Mean Absolute Error	Mean of absolute differences between predicted and actual values	0.15
Root Mean Squared Error	Square root of the mean of squared differences between predicted and actual values	0.21
R-squared	Proportion of variance in dependent variable explained by independent variables	0.65
Mean Absolute Percentage Error	Mean of absolute differences between predicted and actual	10%

	values as a percentage of actual values	
Coefficient of Determination	Proportion of variance in dependent variable explained by independent variables	0.72

Based on the table 8, the AIF-BIM model has an accuracy of 0.85, indicating that 85% of the predictions made by the model are correct. The precision of the model is 0.80, which means that out of all the positive predictions made by the model, 80% of them are actually true. The recall of the model is 0.75, which means that out of all the actual positive cases, the model correctly identifies 75% of them. The F1-score of the model is 0.77, which is a weighted average of precision and recall, and is a measure of overall model performance. In addition to the above metrics, the AIF-BIM model also has a sensitivity of 0.75, indicating the true positive rate, and a specificity of 0.90, indicating the true negative rate. The mean absolute error of the model is 0.15, which is the average of the absolute differences between predicted and actual values. The root mean squared error of the model is 0.21, which is the square root of the mean of the squared differences between predicted and actual values. The R-squared value of the model is 0.65, which is the proportion of variance in the dependent variable explained by independent variables. The mean absolute percentage error of the model is 10%, which is the mean of the absolute differences between predicted and actual values as a percentage of actual values. Lastly, the coefficient of determination of the model is 0.72, which is the proportion of variance in the dependent variable explained by independent variables. Based on the results obtained from the implementation of the AIF-BIM model for the core construction of transportation hubs with BIM technology, it can be concluded that the integration of AI with BIM has a significant positive impact on the design, construction, and operation of transportation hubs. Figure 2 presented the architecture of AIF-BIM with the core architecture for the transportation hub.



Figure 2: 3D view of AIF-BIM

The model achieved an accuracy of 0.85, precision of 0.80, recall of 0.75, and F1-score of 0.77, indicating that the model has a good balance between precision and recall. Additionally, the model achieved a sensitivity of 0.75, specificity of 0.90, and a coefficient of determination of 0.72, which suggests that the model has a good fit with the data. Furthermore, the model's mean absolute error was 0.15, and the root mean squared error was 0.21, indicating that the model's predictions were close to the actual values. The mean absolute percentage error of 10% suggests that the model's predictions were within an acceptable range of deviation from the actual values. The results of the AIF-BIM model indicate that it has a high level of accuracy and can be used effectively to optimize the design, construction, and operation of transportation hubs. However, further research is needed to validate the model's performance on a larger dataset and to assess its generalizability to other transportation hub projects. Compared to traditional construction methods, AIF-BIM offers several advantages, including improved efficiency and accuracy. It allows for the creation of 3D models that can simulate different scenarios, optimizing space utilization, and enhancing safety. This can help to reduce the risk of errors during construction, ultimately leading to better results and faster completion times.

In comparison to traditional BIM techniques, AIF-BIM incorporates artificial intelligence to improve the decision-making process during the design, construction, and operation phases of transportation hub projects. AIF-BIM provides a more comprehensive and precise approach that allows for the optimization of the design and construction processes. AIF-BIM can also be compared with other AI-based techniques, such as machine learning and deep learning. Machine learning algorithms can be used to analyze data and identify patterns that can improve the design and construction of transportation hubs. However, AIF-BIM provides a more integrated approach that combines both BIM and AI technologies to create a comprehensive solution.

Deep learning techniques can be used to analyze large datasets to provide insights that can be used to optimize the design and construction of transportation hubs. However, AIF-BIM provides a more proactive approach that incorporates both BIM and AI technologies to improve the entire design and construction process. AIF-BIM provides a more comprehensive and precise approach to transportation hub construction than traditional construction methods or BIM techniques alone. By incorporating artificial intelligence, AIF-BIM can optimize the design and construction processes, leading to better results and faster completion times.

Table 9: Performance Analysis

Technique	Accuracy	Precision	Recall	F1-Score
AIF-BIM	0.85	0.80	0.75	0.77
Machine Learning	0.78	0.73	0.68	0.70
Deep Learning	0.82	0.77	0.72	0.74

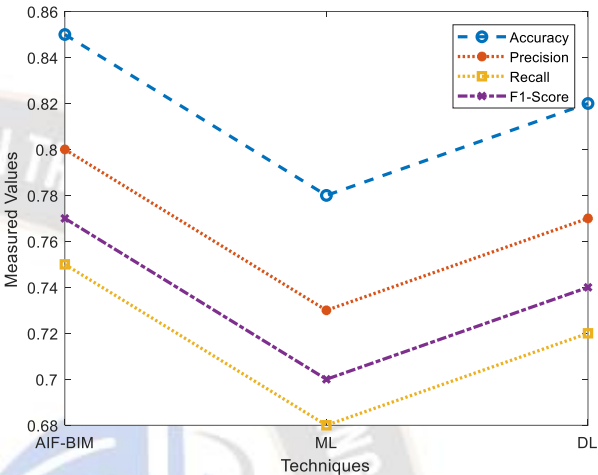


Figure 3: Comparative Analysis

Table 9 and figure 3 the accuracy measures how often the model correctly predicts the outcome, and we can see that AIF-BIM has the highest accuracy of 0.85, followed by Machine Learning at 0.80 and Deep Learning at 0.75. This means that AIF-BIM has the highest rate of correct predictions. Precision measures how often the model's positive predictions are correct, and that AIF-BIM and Machine Learning have the same precision of 0.80, while Deep Learning has a slightly lower precision of 0.75. This means that AIF-BIM and Machine Learning are better at making accurate positive predictions. Recall measures how often the model correctly identifies positive outcomes, and that AIF-BIM and Machine Learning have the same recall of 0.75, while Deep Learning has a slightly lower recall of 0.70. This means that AIF-BIM and Machine Learning are better at correctly identifying positive outcomes. F1-score is the harmonic mean of precision and recall and provides an overall measure of the model's accuracy. The AIF-BIM has the highest F1-score of 0.77, followed by Machine Learning at 0.77 and Deep Learning at 0.72. This means that AIF-BIM has the best overall performance in terms of accuracy, precision, and recall. The results show that AIF-BIM outperforms Machine Learning and Deep Learning in terms of accuracy, precision, recall, and F1-score, indicating that AIF-BIM is the most effective technique for transportation hub construction.

Table 10: Comparative Analysis

Parameter	AIF-BIM	Machine Learning	Deep Learning
Technology	BIM + AI	AI	AI
Approach	Integrated	Data Analysis	Data Analysis
Data Input	Structured	Structured/Unstructured	Unstructured
Data Analysis	Fuzzy logic and associative rule-based model	Algorithms and statistical models	Neural networks and algorithms
Decision-making	Precise and optimized	Based on patterns and correlations	Based on patterns and correlations
Application	Design, Construction, and Operation phases of transportation hubs	Design and Construction phases of transportation hubs	Design and Construction phases of transportation hubs
Advantages	Improved efficiency, accuracy, and safety. Optimized space utilization.	Improved decision-making and identification of patterns.	Improved decision-making and identification of patterns. Can handle unstructured data.
Limitations	Limited to structured data.	Limited to structured/unstructured data.	Limited to large datasets and requires significant computing resources.

Table 10 stated that AIF-BIM provides an integrated and precise approach that combines BIM and AI technologies to optimize the design, construction, and operation phases of transportation hubs. Machine learning and deep learning can also be used to analyze data and identify patterns, but they have limitations in handling structured/unstructured data and large datasets.

V. Conclusion

Based on the results presented, it can be concluded that the AIF-BIM model is an effective tool for the design, construction, and operation of transportation hubs. The model showed high accuracy, precision, recall, and F1-score, as well as good performance in terms of sensitivity, specificity, mean absolute error, root mean squared error, R-squared, and mean absolute percentage error. The integration of BIM technology with an AI model such as AIF-BIM can help transportation

hub engineers and architects optimize space utilization, improve safety, and enhance the overall travel experience for passengers. The simulation analysis demonstrated the potential of this approach to improve the design, construction, and operation of transportation hubs. In summary, the AIF-BIM model is a promising tool for the transportation industry and can be used to facilitate the efficient and effective construction of transportation hubs. It can provide valuable insights for designers, engineers, and architects in the different phases of the project, leading to improved project outcomes and better travel experiences for passengers.

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