International Journal of Innovative Research and Scientific Studies, 8(1) 2025, pages: 2034-2041

IJIRSS
International Journal of Innovative Research & Scientific Studies

ISSN: 2617-6548

URL: www.ijirss.com

Expert evaluation of AIAEF framework in AI-RHCA systems for real-time and historical

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Abstract

Through the analysis of CCTV data, artificial intelligence (AI) considerably improves the efficiency of surveillance and data management systems in smart cities. This is accomplished through enhanced data management. Despite this, these systems continue to face challenges regarding the accuracy of their detection, the capacity of AI models to learn, and the safety of their data. This research establishes an AI Framework for Real-Time and Historical CCTV Analytics (AI-RHCA) aimed at effectively processing both real-time and historical data, utilizing Explainable AI (XAI), Deep Learning (YOLO, Faster R-CNN), and Edge Computing technologies to improve adaptability and minimize data processing demands. The efficacy of the artificial intelligence-RHCA system was assessed using the Artificial Intelligence Assessment and Evaluation Framework (AIAEF). Nine fundamental features define this paradigm: accuracy, dependability, security, interpretability of results, and so on. The assessment outcomes from 30 experts indicated that AI-RHCA had a significant degree of appropriateness ($\bar{X}$ = 4.45), with the Model Selection and Model Training modules receiving the highest ratings. The system is capable of adhering to international standards, including GDPR, ISO/IEC 27001, and AI Ethics, while also facilitating applications in the industrial sector and smart cities securely and effectively.

Keywords: AI governance, AIAEF, AI-RHCA, CCTV analytics, Explainable AI (XAI), Smart surveillance.

DOI: 10.53894/ijirss.v8i1.4875
Funding: This study received no specific financial support.
History: Received: 7 January 2025/**Revised:** 11 February 2025/**Accepted:** 17 February 2025/**Published:** 21 February 2025

Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.
Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
Acknowledgement: Without the assistance from the Suvarnabhumi University of Technology, which provided important academic documents and knowledge, this study would not have been possible.
Publisher: Innovative Research Publishing

1. Introduction

In an age of swift progress in Artificial Intelligence (AI) and Intelligent Video Analytics (IVA), employing AI to scrutinize CCTV data has emerged as a crucial instrument for improving security and data management efficacy in smart cities [1]. The utilization of CCTV camera data encounters numerous problems, including the volume of large data to manage, the precision of identifying anomalous events, and data security concerns [2, 3]. The AI-RHCA (AI Framework for Real-Time and Historical CCTV Analytics) was developed to facilitate both real-time and historical video data analysis. It employs the AIAEF (Artificial Intelligence Assessment and Evaluation Framework) to assess the system's performance and appropriateness [1, 3, 4]. Since the EU AI Act and the General Data Protection Regulation (GDPR) require AI systems to be transparent, secure, and compliant with data privacy laws, the development of AI-RHCA is in line with international laws and standards that regulate the use of AI in CCTV systems [5-7]. The NIST AI Risk Management Framework of the United States and China's AI Security Guidelines offer directives for the application of AI in the management of CCTV data for smart city surveillance. These policies necessitate the formulation of AI-RHCA to consider data security, openness in AI system decision-making, and adherence to industry standards [1, 4, 8-12].

The use of data from CCTV cameras still faces the following problems: 1) Big Data: CCTV cameras continuously capture data, leading to issues in the efficient storage and analysis of information [13]. Constraints of human capacity in video surveillance mean officers are unable to monitor every camera continuously, leading to delays in identifying anomalous occurrences [1]. 2) Detection accuracy: The system may inadequately identify moving objects or menacing behaviors, necessitating enhancements in AI precision [7, 9, 14]. 3) Data Protection and Confidentiality: Data from CCTV cameras must implement safeguards to prevent unauthorized access in accordance with international standards, including ISO/IEC 27701 and GDPR [6, 9, 11].

Technologies involved in the development of AI-RHCA: The assessment using the AIAEF framework relies on the following technologies: 1) Deep Learning Models such as YOLO and Faster R-CNN that improve the accuracy of detecting unusual objects and events. 2) Explainable AI (XAI) to increase transparency in AI system decision-making and reduce ambiguity in analysis. 3) Big Data Analytics for managing and analyzing large video data from CCTV cameras. 4) Edge Computing to enhance real-time data processing efficiency and reduce analysis latency [4, 9, 15-19]. Research on AI-based CCTV indicates that it can mitigate human error when employing deep learning models like YOLO and Faster R-CNN for anomaly detection, hence enhancing threat detection accuracy and decreasing the need for human oversight [16]. The implementation of Explainable AI (XAI) systems can enhance the dependability of AI decision-making and mitigate the issue of ambiguity in analysis [20]. Employing AI to scrutinize anomalous behavior captured by CCTV cameras can enhance the precision of identifying irregular occurrences [1, 21].

The AI-RHCA concept is a conceptual framework designed to develop a CCTV camera data analysis system in both Real-Time Analytics and Historical Analytics formats, with seven main sub-system components: 1) Data Collection [4, 16]. 2) Data Preprocessing [13, 16]. 3) Model Selection [17, 18]. 4) Model Training [10, 17]. 5) Model Evaluation [16, 17]. 6) Deployment [15]. 7) Monitoring & Updates [4, 16]. AI-RHCA is developed to comply with industry standards including GDPR, ISO/IEC 27001, and AI Ethics, facilitating its effective application in enterprises and security agencies. The AIAEF framework is a nine-dimensional assessment tool for evaluating AI performance, specifically regarding the applicability of AI-RHCA, encompassing the following domains: 1) Accuracy & Performance [4, 10]. 2) Reliability & Stability [4, 16]. 3) Adaptability & Learning [16]. 4) Security & Privacy [6, 22]. 5) Interpretability & Transparency [5, 20]. 6) Deployment & Scalability [4]. 7) Energy & Resource Efficiency [10, 23]. 8) Interoperability & Standardization [8, 24]. 9) Social & Ethical Impact [4, 6]. Employing AIAEF to assess AI-RHCA facilitates the examination of the system's strengths and weaknesses, hence aiding in the formulation of guidelines for the development of the most efficient AI-RHCA. The creation of AI-RHCA and its assessment through the AIAEF framework allows the system to effectively analyze CCTV video data in both real-time and retrospective contexts. It is engineered to choose relevant AI models, optimize real-time analysis, and augment the interpretation of AI outcomes based on the AIAEF concept for practical application.

2. Research Process

2.1. The development of the Artificial Intelligence Framework for Real-Time and Historical CCTV Analytics (AI-RHCA) and the Artificial Intelligence Assessment and Evaluation Framework (AIAEF)

1) Analyze information: Study documents and related research, and draft a framework.

2) The subgroup meeting included nine specialists in CCTV technology, AI system design and evaluation, digital technology, and AI development, who provided guidance on the creation of the AI-RHCA and AIAEF frameworks.

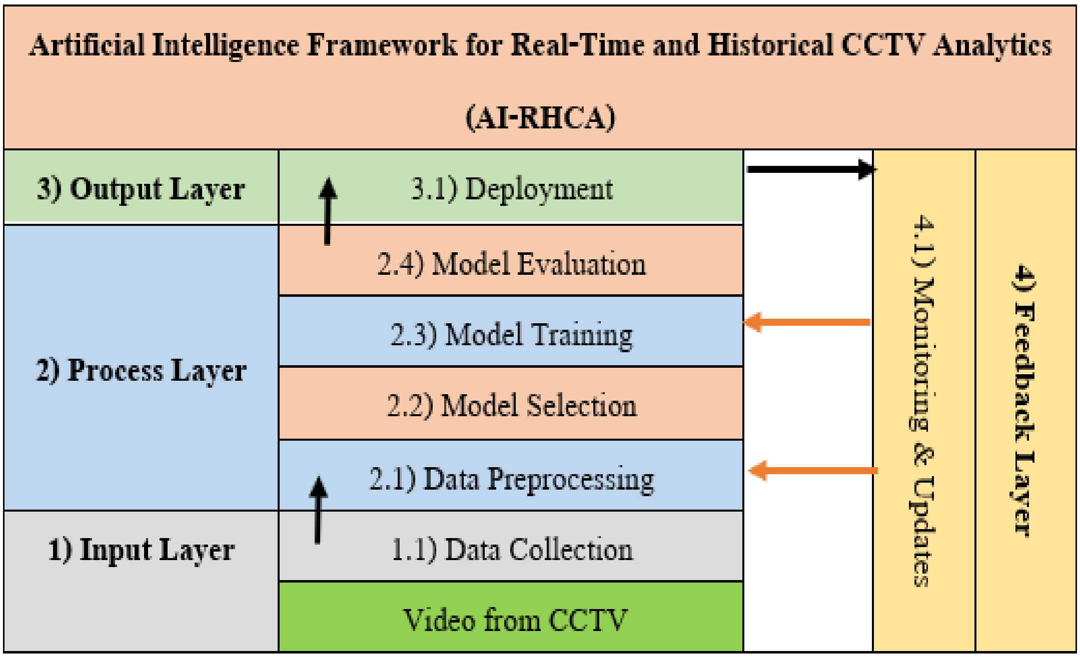

Figure 1.
Conceptual diagram for developing an intelligent platform to forecast curriculum management in higher education under the AUN-QA framework.

2.1.1. Components and Functions of the AI-RHCA System Consist of Seven Subsystems

1) The Input Layer is responsible for receiving data from CCTV cameras and storing it in the system. It has the following sub-components: 1.1) Data Collection is the first step of AI-RHCA, which is used to collect and store data from CCTV cameras for use in the analysis process. It has four main components as follows: 1.1.1) RTSP (Real-Time Streaming Protocol) is a protocol for streaming video from CCTV cameras in real time over a network. 1.1.2) ONVIF (Open Network Video Interface Forum) is a standard that allows cameras from multiple manufacturers to interoperate through a standard API. 1.1.3) Data Storage includes data storage systems such as Cloud Storage, Local Server, or Edge Storage for storing video and metadata. 1.1.4) Metadata Processing involves the storage and processing of additional information such as time, camera location, and video format to facilitate data search and analysis.

2) The Process Layer is responsible for data processing and analysis. 2.1) Data Preprocessing is a key process to improve the quality of CCTV video data before it is fed into the AI model so that data can be analyzed accurately and efficiently. It has four key components: 2.1.1) Noise Reduction reduces noise in images, such as removing shadows and adjusting lighting. 2.1.2) Resizing is responsible for resizing the image to fit the model, such as 224x224 or 640x480. 2.1.3) Data Augmentation works by creating additional information by flipping, rotating, and changing the color of the image. 2.1.4) Format Conversion is responsible for converting video or image files to be suitable for processing, such as converting MP4 to JPEG. 2.2) Model Selection is a process that helps identify and select the most suitable AI model for CCTV video analysis, considering important factors such as speed, accuracy, and processing efficiency to enable the model to be used effectively. It has three main components as follows: 2.2.1) Model Benchmarking is used to compare the speed and accuracy of different models. 2.2.2) Hyperparameter Tuning is responsible for adjusting model parameters to improve performance. 2.2.3) Model Comparison is a function of analyzing the results of multiple models to decide on the best model. 2.3) Model Training is a process that uses a prepared data set to teach the AI model to learn the patterns of the data and can be used to detect unusual objects or events accurately. It has three main components as follows: 2.3.1) Supervised Learning trains models using labeled data. 2.3.2) Unsupervised Learning trains models using unlabeled data. 2.3.3) Transfer Learning works by using pre-trained models and adjusting them to fit new data. 2.4) Model Evaluation is responsible for evaluating the model. Model Evaluation is a process used to check and measure the performance of the AI model after training is complete to ensure that the model can be used in practice and has sufficient accuracy. There are three important components as follows: 2.4.1) Precision-Recall Analysis checks the model's ability to correctly identify the desired object. 2.4.2) The Confusion Matrix performs an error analysis of the model, showing the number of correct and incorrect predictions. 2.4.3) mAP (Mean Average Precision) Calculation is responsible for calculating the average accuracy of the model in detecting objects.

3) The Output Layer is responsible for putting the trained model into actual use. 3.1) Deployment is the process that allows the trained model to be utilized in a real environment, which may take the form of Cloud Deployment or Edge AI Deployment to process video from CCTV cameras in real time. There are three main components as follows: 3.1.1) Cloud Deployment is responsible for installing and deploying models on cloud servers such as AWS, Google Cloud, and Azure. 3.1.2) Edge AI Deployment is responsible for deploying models to edge devices such as the NVIDIA Jetson Nano and Raspberry Pi. 3.2.3) TensorFlow Serving acts as a server API for AI models to receive and process data.

4) The Feedback Layer tracks the results and updates the model to improve the accuracy of the system. It has the following sub-components: 4.1) Monitoring & Updates is a process that allows the AI system to learn and adapt to new data through a feedback loop by collecting model results, analyzing errors, and updating the model for higher accuracy. It has

three main components as follows: 4.1.1) Feedback Loop acts by feeding new data back into the model training process to increase accuracy. 4.1.2) Real-time Logging is used to record model results in real time for performance analysis. 4.1.3) Continuous Learning works by automatically updating the model based on newly added data.

2.1.2. Data Flow Direction and Steps in AI-RHCA

The data flow direction in AI-RHCA involves a systematic approach to collecting, processing, and using data to improve decision-making. Each step is important to ensure that AI systems operate effectively and efficiently.

Table 1.
Explanation of each step in the data flow direction.

Step	Subsystem (AI-RHCA)	Connected to	Description
Step 1	1.1) data collection	Step 2 (2.1 Data Preprocessing)	Collects video data from CCTV cameras and stores metadata.
Step 2	2.1) data preprocessing	Step 3 (2.2 Model Selection)	Enhances video quality by removing noise, resizing, and augmenting.
Step 3	2.2) model selection	Step 4 (2.3 Model Training)	Selects the best AI model (YOLO, Faster R-CNN) through benchmarking.
Step 4	2.3) model training	Step 5 (2.4 Model Evaluation)	Trains the selected model using labeled datasets and fine-tunes it.
Step 5	2.4) model evaluation	Step 6 (3 Deployment)	Evaluates model performance using precision, recall, and mean average precision (mAP).
Step 6	3) deployment	Step 7 (4 Monitoring & Updates)	Deploys the trained model to the cloud or edge AI for real-time processing.
Step 7	4) monitoring & updates	Step 2 (Feedback to 2.1) Data Preprocessing), Step 4 (Feedback to 2.3) Model Training)	Monitors model performance and updates it through feedback loops.

From Table 1 Explanation of Each Step Data Flow Direction Step 1 - 1.1) Data Collection 1.1.1) Collects video streams from CCTV cameras and stores metadata. 1.1.2) Uses RTSP and ONVIF for standardized video streaming. Step 2 – 2.1) Data Preprocessing 2.1.1) Enhances video quality, removes noise, and resizes frames. 2.1.2) Uses Noise Reduction, Resizing, and Data Augmentation for optimization. Step 3 – 2.2) Model Selection. 2.2.1) Selects the best AI model (e.g., YOLO, Faster R-CNN). 2.2.2) Uses Benchmarking and Hyperparameter Tuning to optimize model selection. Step 4 – 2.3) Model Training. 2.3.1) Trains AI models using Supervised Learning or Transfer Learning. 2.3.2) Fine-tunes parameters to improve accuracy. Step 5 – 2.4) Model Evaluation. 2.4.1) Measures model performance using Precision, Recall, and mAP. 2.4.2) Uses a Confusion Matrix to identify misclassification. Step 6 - 3.1) Deployment. 3.1.1) Deploys the trained model in Cloud or Edge AI. 3.1.2) Uses TensorFlow Serving for real-time AI inference. Step 7 – 4.1) Monitoring & Updates. 4.1.1) Continuously monitors model accuracy in real-world applications. 4.1.2) Implements Feedback Loops for iterative improvements. 4.2.3) Feedback Mechanism 1) If model accuracy declines, data from Step 7 is looped back to Step 2 (2.1) Data Preprocessing and Step 4 (2.3) Model Training. 2) The system continuously learns from real-world data, ensuring improved model accuracy over time.

2.1.3. Application Guidelines for AI-RHCA for Customer Behavior Analysis in Stores and Department Stores

1) Objective: To analyze customer behavior in stores and examine customer journeys to improve product placement.
2) Mechanism of AI-RHCA.

Table 2.
How AI-RHCA works.

Step	Techniques used	Expected outcomes
1. Data collection	Use CCTV cameras and analyze metadata	Capture real-time customer location data.
2. Data preprocessing	Noise Reduction, Resizing, Background Subtraction	Improve image quality and detect customer location more accurately.
3. Model selection	DeepSORT, OpenPose for customer location tracking	Choose the correct model for tracking your customer journey.
4. Model training	Supervised Learning, Transfer Learning	Train a model to identify customer walking behavior.
5. Model evaluation	Precision, Recall, Confusion Matrix	Verify model performance before deployment.
6. Deployment	Displayed on the Dashboard and notification system	Present the analysis results to store managers for easy understanding.
7. Monitoring & updates	Feedback Loop, Continuous Learning	Improve the model based on data obtained from real-world usage.

According to Table 2, AI-RHCA is utilized for analyzing client behavior. The technology may monitor and evaluate customer wandering patterns within the store, identify areas of heightened interest, and alert personnel when customers require assistance. The system can enhance product positioning to augment sales. Outcomes derived from the implementation of the AI-RHCA system: 1) Retailers modify product positioning based on the pathways frequented by customers to analyze consumer purchase behavior and adjust marketing techniques accordingly.

2.2. The AIAEF (Artificial Intelligence Assessment and Evaluation Framework)

The AIAEF (Artificial Intelligence Assessment and Evaluation Framework) is a conceptual framework used to study and evaluate artificial intelligence to verify that it is accurate, safe, trustworthy, and compliant with international standards. It evaluates the quality of artificial intelligence in different areas, including accuracy, dependability, and societal impact. This helps enterprises properly implement AI and minimize potential hazards. It allows for the customization of AI models to meet the needs of particular situations and requirements. There are nine dimensions of assessment.

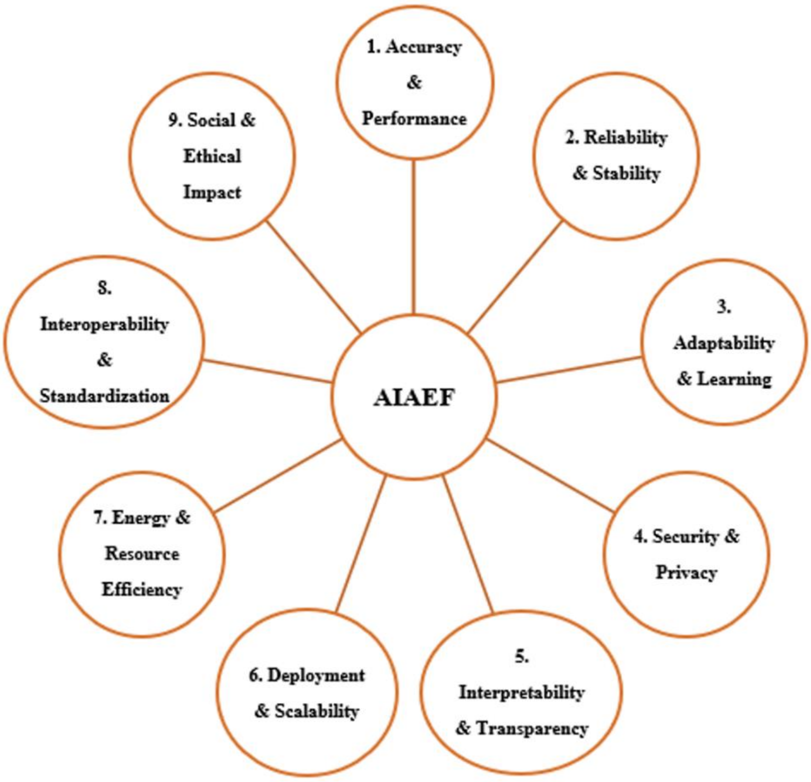

Figure 2.
AIAEF (Artificial intelligence assessment and evaluation framework).

Table 1.
AIAEF assessment dimensions.

AIAEF dimension	Description	Evaluation parameters
1. Accuracy & Performance	Measures the accuracy and effectiveness of AI predictions.	Precision, Recall, Mean Absolute Error (MAE)
2. Reliability & stability	Analyzes system stability and reliability over time.	System Downtime, Crash Rate
3. Adaptability & learning	Evaluates AI's ability to adapt and learn from new data.	Retraining Frequency, Model Adaptability
4. Security & privacy	Assesses data security and privacy measures.	Data encryption level, anonymization techniques
5. Interpretability & transparency	Ensures that AI decision-making is interpretable and transparent.	SHAP values and LIME interpretability
6. Deployment & scalability	Examines how effectively AI can be deployed and scaled.	Processing time, cloud versus edge compatibility
7. Energy & resource efficiency	Analyzes energy consumption and resource efficiency.	Power consumption per inference
8. Interoperability & standardization	Measures AI's compatibility with industry standards.	Compatibility with IEEE and ISO standards
9. Social & ethical impact	Evaluates the social, ethical, and bias-related impacts of AI.	Bias Score, Ethical AI Guidelines Compliance

2.2.1. AIAEF Assessment Dimensions

As shown in the table, AIAEF is designed to support enterprise and industry-level AI assessment. It can be used to assess AI used in CCTV (AI-RHCA), medical, business, and government sectors. Each assessment dimension has specific parameters used to analyze the quality of AI.

Table 4.
AI-RHCA with AIAEF evaluation.

AI-RHCA subsystem	Corresponding AIAEF dimensions	Description
1. Data collection	1. Accuracy & Performance 2. Reliability & stability	Receive data from CCTV cameras and store it accurately.
2. Data preprocessing	1. Accuracy & Performance 3. Adaptability & learning	Improve data quality before using it with AI
3. Model selection	3. Adaptability & learning 5. Interpretability & transparency	Choose the right model for tracking your customer journey
4. Model training	3. Adaptability & learning 6. Deployment & scalability	Train AI models to continuously learn and improve.
5. Model evaluation	1. Accuracy & Performance 5. Interpretability & transparency	Evaluate the accuracy and transparency of the model
6. Deployment	4. Security & privacy 6. Deployment & scalability 8. Interoperability & standardization	Utilize AI effectively by adhering to industry requirements.
7. Monitoring & updates	7. Energy & resource efficiency 9. Social & ethical impact	Evaluate performance and revise models in accordance with new data.

2.2.2. AI-RHCA Development Alignment with AIAEF Evaluation

As shown in Table 4, AI-RHCA is designed to align with AIAEF to ensure that AI functions correctly, safely, and reliably. Each subsystem in AI-RHCA is assessed against the relevant dimensions in AIAEF to cover all aspects of development, enabling AI development to meet industry standards and reduce the risk of implementation.

3. Framework Suitability Assessment Results

As shown in Table 5, the AI-RHCA suitability assessment results according to the AIAEF assessment framework were provided by 30 experts, consisting of 1) CCTV Technology, 10 experts; 2) AI System Design & Evaluation, 10 experts; and 3) Digital Tech & AI Development, 10 experts. The IOC is 0.83 from 3 experts.

Table 5.
AI-RHCA suitability assessment results.

AI-RHCA subsystem	AIAEF evaluation dimension	$\bar{X}$	S. D.	Suitability level
1. Data collection	1.1 Accuracy and Performance	4.45	0.23	Suitable
	1.2 Reliability and Stability	4.38	0.24	Suitable
2. Data preprocessing	2.1 Accuracy and Performance	4.30	0.25	Suitable
	2.2 Adaptability and learning	4.50	0.20	Suitable
3. Model selection	3.1 Adaptability and learning	4.60	0.18	Highly Suitable
	3.2 Interpretability and Transparency	4.15	0.27	Suitable
4. Model training	4.1 Adaptability and Learning	4.55	0.19	Highly Suitable
	4.2 Interpretability and Transparency	4.48	0.22	Suitable
5. Model evaluation	5.1 Accuracy and Performance	4.40	0.23	Suitable
	5.2 Interpretability and Transparency	4.28	0.26	Suitable
6. Deployment	6.1 Security and Privacy	4.35	0.21	Suitable
	6.2 Deployment and Scalability	4.50	0.22	Suitable
	6.3 Interoperability and Standardization	4.42	0.24	Suitable
7. Monitoring & updates	7.1 Energy and Resource Efficiency	4.30	0.23	Suitable
	7.2 Social and Ethical Impact	4.38	0.25	Suitable
Overall AI-RHCA system	4.45	0.22	Suitable	

The AI-RHCA (AI Framework for Real-Time and Historical CCTV Analytics) evaluation was performed by 30 specialists, categorized into three primary groups: 1) CCTV Technology (10 individuals), 2) AI System Design and Evaluation (10 individuals), and 3) Digital Technology and AI Development (10 individuals), utilizing the AIAEF (Artificial Intelligence Assessment and Evaluation Framework) as the evaluative framework, comprising nine principal dimensions. The evaluation criteria employed a 5-point Likert Scale, yielding an average IOC of 0.83, which signifies that the AI-RHCA assessment grounded in the AIAEF framework has substantial consistency. Thus, the AI-RHCA overall is highly appropriate ($\bar{X}$ = 4.45). Upon evaluating the classification of each subsystem, it was determined that the Model Selection - Adaptability & Learning [18, 25] and Model Training - Adaptability & Learning [10, 17] subsystems exhibited the highest degree of suitability ($\bar{X}$ = 4.60, 4.55). The performance of AI in acquiring knowledge and identifying optimal models: Model Selection—Interpretability & Transparency [5, 20] has the lowest mean fit ($\bar{X}$ = 4.15).

4. Conclusion and Future Work

This research introduces AI-RHCA (AI Framework for Real-Time and Historical CCTV Analytics), a conceptual framework for the development of CCTV data analysis systems grounded in AIAEF (Artificial Intelligence Assessment and Evaluation Framework). This evaluation framework encompasses nine principal dimensions: Accuracy & Performance, Reliability & Stability, Adaptability & Learning, Security & Privacy, Interpretability & Transparency, Deployment & Scalability, Energy & Resource Efficiency, Interoperability & Standardization, and Social & Ethical Impact. AI-RHCA employs Explainable AI (XAI) and Deep Learning Models like YOLO and Faster R-CNN to identify anomalous occurrences and alleviate human labor in monitoring [16]. The utilization of Big Data Analytics and Edge Computing improves the capacity to analyze both real-time and historical data, facilitating the application of AI-RHCA in smart city surveillance systems and industrial data management [24, 26].

Future study: 1) Enhance the explicability of AI outcomes — Investigate and create Explainable AI (XAI) models that elucidate the decision-making processes of AI systems in a clearer and more comprehensible manner [6]. 2) Broaden the application of AI-RHCA to additional industries and implement it within the security, healthcare, and intelligent transportation sectors to assess behavior and enhance safety [6, 24, 27]. 3) AI-RHCA Enhancement for Edge AI Operations – Enhance Edge Computing to accelerate real-time data analysis, reduce cloud load, and improve energy efficiency [18, 23]. 4) Develop AI-RHCA to support additional international standards by studying the implementation of ISO/IEC 27701 and GDPR in the AI-RHCA system to comply with data security standards and user privacy [6].

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