



Al in Architectural Acoustics

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Abstract - This paper explores a potential framework for applying Artificial Intelligence (AI) in acoustic consulting, focusing on the automated analysis of architectural drawings to determine key project criteria. Acoustic consultants currently typically rely on visual interpretation of architectural drawings to establish criteria for internal noise levels, reverberation time, and acoustic separation, which can be both time consuming and error prone. The proposed AI framework aims to automate this process by using computer vision and machine learning techniques to identify and extract relevant features, such as room names, room layouts, as well as architectural elements such as doors, glazing, partitions, and finishes. By leveraging these technologies, the framework seeks to enhance the efficiency, accuracy, and consistency of acoustic analysis, enabling consultants to make more informed decisions. The paper discusses the components of this framework, the potential benefits and challenges of its implementation, and suggests proof-of-concept tests to validate its effectiveness.

1 INTRODUCTION

Acoustic consulting plays an essential role in building design, ensuring spaces meet the necessary standards for sound quality and noise control. The initial process involves determining acoustic criteria related to internal noise levels, reverberation time, and acoustic separation. Currently, this is largely achieved through visual interpretation of architectural drawings, a time-consuming and labour-intensive task that relies heavily on the expertise of the acoustic consultant. Given the complexity and variety of architectural plans, there is a growing interest in exploring how new technologies, particularly Artificial Intelligence (AI), could enhance the efficiency and accuracy of these tasks.

Al has the potential to transform many aspects of architectural and engineering processes, yet its application in acoustic consulting remains largely unexplored. This paper proposes a potential framework for using Al to assist acoustic consultants by automating the analysis of architectural drawings. The aim is to develop a system capable of identifying and extracting relevant features, such as room names, doors, glazing, partitions, and finishes, that are used to determine acoustic criteria and impact the resultant acoustic performance of a space. By leveraging Al techniques such as computer vision and machine learning, this framework could potentially reduce the time and effort required for manual interpretation, improve the consistency and accuracy of outcomes, and allow consultants to focus on higher-level design considerations.

The proposed framework involves several key components: preprocessing architectural drawings to standardise formats and enhance image quality; employing computer vision algorithms to detect and classify relevant features; and using machine learning models to interpret this data to establish appropriate acoustic criteria. Additionally, integrating this AI tool with existing consulting workflows would be crucial to ensure its practical application in real-world scenarios.

By investigating this potential AI framework, the paper aims to provide a foundation for further research and development in this emerging area, with the ultimate goal of improving the efficiency, accuracy, and outcomes of acoustic consulting practices.



2 CURRENT PRACTICES

Acoustic consulting is an essential component of the building design process, particularly in environments where sound quality and noise control are critical, such as schools, hospitals, offices, and residential buildings. The primary objectives in acoustic consulting are to ensure compliance with regulatory standards and/or relevant guidance documents, and to create acoustically comfortable spaces that meet client expectations. To achieve these objectives, acoustic consultants must determine criteria related to internal noise levels, reverberation time, and acoustic separation, which are largely influenced by the building's architectural design.

2.1 Current Practices

The current practice for acoustic consultants typically begins with a thorough review of architectural drawings and documentation to identify relevant details that may influence acoustic performance. This includes examining room dimensions, layout, material finishes, and building components such as doors, windows, walls, and ceilings. The process is highly manual and requires expertise to interpret the architectural symbols and annotations correctly.

Consultants often use specialised software tools, such as computer-aided design (CAD) viewers, to visualise these drawings and make manual measurements. However, the extraction of information necessary to determine acoustic criteria, such as the room type and function and spatial relationships between rooms, remains a manual and time-consuming effort. Furthermore, the reliance on human interpretation introduces variability and the potential for errors or inconsistencies, especially in complex projects with a large number of drawings.

2.2 Limitations of Current Practices

The manual nature of current practices presents several limitations:

Time-Consuming Process: Extracting and interpreting relevant acoustic information from architectural drawings is labour-intensive, requiring hours or even days depending on the project's complexity and scale.

Inconsistent Outcomes: Human interpretation can vary between consultants, leading to inconsistencies in identifying critical elements that affect acoustic criteria. This variability can result in different outcomes for similar projects, potentially impacting design quality and client satisfaction.

Limited Efficiency in Handling Large Datasets: Modern architectural projects often involve numerous revisions and multiple design iterations. Keeping track of these changes and updating acoustic assessments manually can be challenging, time consuming, and prone to oversight.

High Dependency on Expertise: The current process requires significant experience and expertise to accurately interpret complex architectural drawings, making it difficult for less experienced consultants to achieve consistent results.

2.3 The Role of Al in Acoustic Consulting

Artificial Intelligence, particularly in the fields of computer vision and machine learning, offers a promising solution to the limitations of current practices. All can automate the analysis of architectural drawings by recognising and extracting relevant features that impact acoustic performance. This capability should allow for more consistent, accurate, and faster determination of acoustic criteria.

Al tools can be trained to recognise patterns and symbols in architectural drawings, such as room names, doors, glazing types, and separating partitions. Machine learning algorithms can learn from a dataset of annotated drawings to improve their recognition accuracy over time. Furthermore, Al could be used to identify complex relationships between building components that affect acoustics, such as the adjacency of rooms and the materials used in walls and ceilings.

2.4 Potential Benefits of AI in Acoustic Consulting

By incorporating AI into acoustic consulting, several benefits can be realised:

Improved Efficiency: Automating the extraction of acoustic-relevant information from drawings can significantly reduce the time required for initial assessments, allowing consultants to focus on higher-level design considerations and client interactions.

Enhanced Accuracy and Consistency: Al tools can reduce human error and variability, leading to more consistent outcomes across different projects and consultants.

Scalability for Large Projects: All systems can efficiently handle large datasets and frequent revisions, ensuring that acoustic assessments remain up-to-date with the latest design changes.

Knowledge Transfer and Training: Al tools can assist less experienced consultants by providing automated insights and suggestions based on the analysis of architectural drawings, thereby supporting professional development and reducing dependency on individual expertise.

2.5 Challenges and Considerations for Al Implementation

While the benefits of AI in acoustic consulting are compelling, there are also challenges and considerations to address. These include the need for high-quality training data, the complexity of integrating AI tools with existing workflows and software, and ensuring that AI systems are interpretable and transparent to users. Additionally, concerns around data privacy, security, and the ethical implications of AI decision-making must be carefully managed.

The following sections will explore the methodology for implementing AI in the analysis of architectural drawings and demonstrate how these tools can be practically applied to determine acoustic criteria, highlighting both the potential benefits and challenges involved.

3 AI METHODOLOGY FOR ANALYSING ARCHITECTURAL DRAWINGS

This section outlines the potential AI methodology to assist acoustic consultants in analysing architectural drawings. The objective is to automatically identify and extract relevant information that affects the acoustic criteria of a project, specifically focusing on internal noise levels, reverberation time, and acoustic separation. The methodology suggests computer vision and machine learning techniques to process architectural drawings and derive meaningful data for acoustic analysis.

3.1 Overview of the Al Framework

The proposed Al framework consists of three main components:

- **1. Preprocessing:** Preparing architectural drawings for Al analysis by enhancing image quality, normalising formats, and segmenting different drawing components.
- **2. Feature Extraction:** Using computer vision algorithms to identify and extract relevant architectural aspects, such as room names, room dimensions, doors, glazing, separating partitions, and ceiling and floor finishes.
- **3. Data Analysis and Interpretation:** Applying machine learning models to interpret extracted features, determine their acoustic relevance, and assist in establishing the project criteria.

3.2 Preprocessing of Architectural Drawings

The preprocessing step ensures that the input data is in a suitable format for analysis. Architectural drawings can vary widely in terms of file format, scale, resolution, and graphical complexity. To standardise these inputs, the following preprocessing techniques can be applied:

Format Conversion: Drawings are converted into a uniform digital format, such as high-resolution images (e.g., TIFF or PNG) or vector graphics (e.g., SVG), to facilitate consistent processing by AI algorithms.

Image Enhancement: Techniques such as contrast adjustment, noise reduction, and edge sharpening can be used to enhance the clarity of lines, symbols, and text within the drawings. This step can help improve the accuracy of feature extraction by making critical elements more distinguishable.

Segmentation: The drawing can be segmented into different layers corresponding to various architectural elements, such as structural walls, partitions, doors, and furniture. This segmentation allows the AI model to focus on specific components during analysis, reducing computational complexity and improving recognition accuracy.

3.3 Feature Extraction Using Computer Vision

The feature extraction component is responsible for identifying and extracting architectural elements that influence acoustic performance. This process involves the use of advanced computer vision techniques, such as object detection, optical character recognition (OCR), and semantic segmentation.

Object Detection: Object detection algorithms, such as Convolutional Neural Networks (CNNs) or You Only Look Once (YOLO) models, can be employed to identify and locate key architectural features within the drawings. These features include room names, doors, windows, and partitions. The models can be trained on large datasets of annotated architectural drawings to recognise and differentiate between various symbols and notations.

Optical Character Recognition (OCR): OCR technology can be used to extract textual information from the drawings, such as room names, dimensions, and annotations. This information is essential for determining the function of each space and its corresponding acoustic requirements. The OCR model is trained to recognise a wide range of fonts and text orientations typically found in architectural drawings.

Semantic Segmentation: Semantic segmentation techniques can be used to classify each pixel in the drawing according to its corresponding architectural element (e.g., walls, doors, glazing, etc.). This step allows for a detailed understanding of the spatial relationships between different elements, which is critical for determining acoustic separation and reverberation time.

3.4 Data Analysis and Interpretation Using Machine Learning

Once the relevant features have been extracted, the next step is to analyse and interpret this data to determine the acoustic criteria. This involves using machine learning models to assess the identified features and their relevance in determining internal noise levels, reverberation time, and acoustic separation criteria.

Classification Models: The use of supervised learning algorithms, such as Support Vector Machines (SVM) or Random Forests, can be used to classify different spaces (e.g., offices, classrooms, meeting rooms) based on their acoustic requirements. These models would be trained on a dataset that correlates specific room types with predefined acoustic criteria, such as maximum permissible noise levels or desired reverberation times.

Regression Models: Regression techniques can be applied to predict numerical values, such as the estimated reverberation time or sound transmission loss, based on the extracted features. For example, a regression model can estimate the reverberation time for a room by considering factors such as room volume and surface materials.

Spatial Analysis Models: Graph-based models or spatial clustering techniques can be employed to analyse the spatial relationships between different elements, such as the adjacency of rooms or the placement of doors and windows. These models help assess the acoustic separation between spaces and identify potential pathways for sound transmission.

3.5 Training and Validation of Al Models

The development of the AI tool would require a comprehensive training and validation process to ensure it performs accurately across a range of scenarios. A diverse dataset of annotated architectural drawings would be essential, covering various building types (e.g., residential, commercial, educational), as well as various drawing conventions as different architects draw things slightly differently.

Training would involve a combination of supervised and unsupervised learning techniques. Supervised learning would be used to teach the models to recognise and classify specific features based on labelled data. Meanwhile, unsupervised learning methods, such as clustering, could identify patterns and relationships in the data that are not explicitly labelled. Cross-validation and testing on separate datasets would be crucial to evaluate the performance of the models, ensuring they provide accurate and reliable outputs.

3.6 Integration with Existing Acoustic Consulting Workflows

To ensure the practical application of the Al tool, the framework considers how it could be integrated into existing acoustic consulting workflows and software environments. A user-friendly interface would be essential to display the identified features, highlight potential acoustic issues, and suggest criteria adjustments, supporting consultants without disrupting their established practices.

3.7 Summary

This proposed framework outlines the potential components and processes for developing an AI tool to assist in the analysis of architectural drawings for acoustic consulting. By integrating computer vision for feature extraction with machine learning for data analysis, this framework aims to create a robust system that could improve the efficiency, accuracy, and consistency of determining acoustic criteria.

4 APPLICATION OF AI METHODOLOGY TO DETERMINE ACOUSTIC CRITERIA

This section explores the potential application of the proposed AI framework in determining acoustic criteria for building projects. By automating the analysis of architectural drawings, the AI tool could identify and extract critical information to determine internal noise levels, reverberation time, and acoustic separation criteria, as well as determining specific acoustic requirements for building elements (e.g Rw for partitions, doors, glazing and NRC for surface finishes)

. This framework aims to streamline the initial assessment process, enhance accuracy, and reduce the time and effort required in the delivery of concept design inputs.

4.1 Determining Internal Noise Level Criteria

Internal noise levels refer to the acceptable sound levels within a specific space, considering both external and internal noise sources. The Al tool could determine the criteria by identifying the building type (school, office etc.), extracting the room names, classifying the room function, and identifying relevant guidance documents to determine each room's internal noise level criteria.

Room Type Identification: The AI tool would first classify each room according to its function (e.g., office, classroom, corridor) using a combination of object detection and OCR techniques.

Determine Criteria: Based on the room function, the AI tool can then reference relevant Standards or guidance documents. The AI tool would then populate a table with the relevant room types and internal noise level criteria for inclusion in the acoustic report or architectural markup plan.

4.2 Determining Reverberation Time Criteria

Reverberation time is a key factor in the acoustic quality of a space, particularly in areas like classrooms, auditoriums, and meeting rooms, where speech intelligibility is crucial. The AI tool can be used to estimate the reverberation time of each room by analysing relevant architectural features.

Room Type Identification: The same room type identification used to determine the internal noise level criteria is applied to determine the reverberation time criteria. Also, room dimensions can be identified to determine criteria based on room volumes, where relevant.

Determine Reverberation Time Criteria: Based on the room function, type and/or volume, the AI tool can then reference relevant Standards or guidance documents. The AI tool would then populate a table with the relevant room types and reverberation time criteria for inclusion in the acoustic report or architectural markup plan.

4.3 Determining Acoustic Separation Criteria

Acoustic separation focusses on minimising sound transmission between adjacent spaces, to maintain privacy and reduce noise disturbance. The separation criteria are typically determined based on the anticipated noise level in the source room and the tolerance of users in the receiving room. The Al tool can determine the acoustic separation criteria by examining the spatial relationships between rooms.

Identification of Separating Elements: The AI tool would use object detection algorithms to identify and categorise elements that separate spaces, such as walls, doors, glazing and floors.

Assessment of Adjacency and Spatial Relationships: The framework would employ spatial analysis models to understand the adjacency and layout of different rooms, such as which spaces are next to each other or stacked vertically. This spatial analysis aims to identify the room adjacencies that require specification of acoustic separation, such as between Sole Occupancy Units in a residential development, or between offices in a commercial development.

Determine Acoustic Separation Criteria: Based on the identified room adjacencies, the Al tool references the relevant Standard or guidance document to determine the required level of separation between spaces. This can be detailed in a table for inclusion in the acoustic report, or overlayed on the architectural markup plans.

5 ADDITIONAL REVERBERATION TIME ASSESSMENT ASSISTANCE

The Al tool could also be used to extract relevant information used in the prediction the reverberation time, providing further efficiencies in project delivery.

Surface Material Analysis: The tool can be trained to recognise different surface materials on walls, ceilings, and floors using semantic segmentation techniques. By understanding the material properties, the AI could estimate their sound absorption coefficients based on referenced measurement data and use these inputs to predict the reverberation time.

Room Geometry and Volume Calculation: The Al tool can analyse the dimensions of each room and calculate the total volume.

Prediction of Reverberation Time: Using established prediction methods, the AI can calculate the reverberation time for each space based on the room's volume and surface materials. The tool could then highlight rooms that require additional acoustic treatments to meet the desired reverberation time criteria.

6 LEVERAGING THE RAPIDLY EVOLVING LANDSCAPE OF AI DEVELOPMENT

The landscape of AI is evolving at an unprecedented pace, with continuous advancements in computer vision and machine learning technologies that hold significant promise for the development of an AI tool for acoustic consulting. Recent breakthroughs in AI have made it feasible to automate complex tasks such as the analysis of architectural drawings, which was previously reliant on human expertise.

Several computer vision and machine learning technologies show particular promise for developing an Al tool that can analyse architectural drawings and determine acoustic criteria:

6.1 Computer Vision Tools

Convolutional Neural Networks (CNNs): CNNs are highly effective for image recognition tasks and could be used to identify key architectural elements such as room names, doors, windows, and partitions. Pre-trained models like VGGNet, ResNet, and EfficientNet are widely available and could serve as a starting point for training on architectural datasets.

You Only Look Once (YOLO) and Single Shot MultiBox Detector (SSD): These are advanced object detection algorithms that provide real-time object detection capabilities. YOLO and SSD could be employed to detect and classify multiple objects within a drawing simultaneously, for identifying numerous architectural elements in a complex floor plan.

Optical Character Recognition (OCR) Tools: OCR tools such as Tesseract, Google Vision API, or Microsoft Azure OCR are designed to extract textual information from images. These tools can be used to read text annotations in architectural drawings, such as room names, dimensions, and other relevant notes to determine acoustic criteria.

Semantic Segmentation Models: Models like U-Net or DeepLab are specifically designed for pixel-level image classification. These models could be used to segment architectural drawings into different components (e.g., walls, doors, glazing) to understand spatial relationships and material properties, to determine acoustic criteria and treatment requirements.

6.2 Machine Learning Tools

Support Vector Machines (SVM) and Random Forests: These supervised learning algorithms are well-suited for classifying different types of rooms or spaces based on their acoustic requirements. By training on a dataset that maps specific room types to acoustic criteria, these models could help automate the decision-making process.

Graph Neural Networks (GNNs) and Spatial Analysis Models: GNNs and spatial clustering techniques could be utilised to analyse the spatial relationships between different elements within a building, such as the adjacency of rooms. These models are particularly useful for assessing acoustic separation and identifying potential pathways for sound transmission.

Transformer Models: Transformer-based models, such as Vision Transformers (ViTs) and text-based transformers like BERT, can be leveraged for multimodal analysis, integrating both visual and textual data from architectural drawings to provide a comprehensive assessment.

7 PROOF OF CONCEPT TESTS USING CHATGPT

To validate the proposed AI framework, several proof-of-concept tests can be conducted using existing AI tools and models. These tests aim to demonstrate the feasibility of the AI tool's core functionalities, such as feature extraction, classification, and prediction, before developing a fully customised solution. The following tests can be undertaken using platforms like ChatGPT or other available AI tools:

7.1 Test 1: Architectural Feature Recognition

To explore the feasibility of using AI for architectural feature recognition, a Custom GPT model was developed and tested as a proof of concept. The primary objective of this test was to evaluate the model's ability to analyse architectural drawings and automatically extract features relevant to acoustic consulting, such as room names, doors, and glazed elements.

The Custom GPT demonstrated partial success in recognising certain architectural features. Specifically, it was effective in accurately extracting room names from the drawings. This capability shows promise in automating the classification of spaces based on their function, which is crucial for determining acoustic criteria like internal noise levels and reverberation time.

However, the test also revealed several limitations in the model's current performance. The GPT relies on text labels within the drawings to identify the number of doors, which means it only counts doors that are explicitly labelled. As a result, any doors without a corresponding label are not detected, leading to incomplete data extraction. Additionally, the GPT was not successful in identifying glazed elements.

These limitations suggest that while the GPT shows potential in specific tasks, such as text recognition, it may not yet be fully suited for comprehensive architectural feature recognition. The test indicates that other computer vision tools, such as Convolutional Neural Networks (CNNs) for object detection or semantic segmentation models for pixel-level classification, could offer more robust solutions. Further development and integration of these advanced tools could enhance the overall effectiveness and reliability of an Al-driven approach to feature recognition.

7.2 Test 2: Classification of Room Types

A second proof of concept test was conducted using a Custom GPT model to classify rooms based on their names and functions. The goal of this test was to evaluate the model's ability to interpret room names extracted from architectural drawings and categorise them according to predefined acoustic uses as outlined in AS/NZS 2107:2016.

The Custom GPT successfully extracted room names from the architectural drawings and generated a comprehensive list of room functions. Leveraging this information, the model accurately classified the rooms according to their specific functions, such as offices, classrooms, corridors, and meeting rooms. These classifications were directly aligned with the categories and acoustic criteria recommended by AS/NZS 2107:2016, demonstrating the model's capability to interpret and apply standards-based guidelines.

This test shows that Custom GPT can effectively automate the room classification process, a critical task in determining acoustic requirements like internal noise levels and reverberation times. The successful outcome suggests that AI tools, such as Custom GPT, have potential in streamlining the initial stages of acoustic analysis by quickly and accurately categorising spaces according to standardised acoustic criteria. This functionality could reduce the time required for manual classification and enhance consistency in the application of acoustic standards across different projects.

While the Custom GPT demonstrated robust performance in room classification, further refinement and integration with additional AI tools could enhance its capacity to handle more complex scenarios, such as multi-purpose spaces or rooms with ambiguous names. Nonetheless, the results from this proof of concept provide a solid foundation for further development and validation of AI-driven approaches in acoustic consulting.

7.3 Test 3: Identifying Room Adjacencies

A third proof of concept test was conducted using a Custom GPT model to identify room adjacencies within architectural drawings. The objective of this test was to assess the model's ability to determine which rooms are adjacent to each other, a critical task for specifying the required acoustic separation performance between spaces.

The results of this test were only partially successful. While the Custom GPT was able to identify some room adjacencies, it frequently generated incorrect adjacency lists, failing to accurately map the spatial relationships between rooms. This limitation likely stems from the model's current inability to effectively interpret the geometric and spatial layout of the floor plans, particularly in complex drawings where room boundaries are not straightforward or where adjacency relies on a precise understanding of the spatial arrangement.

The test highlighted that while Custom GPT could partially recognise spatial relationships, its performance in this area needs significant improvement to be reliably used in practical applications.

These findings suggest that enhancing the model's spatial analysis capabilities may require integrating additional Al tools, such as Graph Neural Networks (GNNs) or advanced computer vision techniques, to better interpret the spatial context and relationships within architectural drawings. By combining the strengths of these tools, a more robust solution for accurately identifying room adjacencies could be developed.

The Custom GPT model was, however, able to successfully provide minimum acoustic separation performance requirements for each room type, referencing the AAAC Guideline for Commercial Building Acoustics, which could be used in the acoustic report or assist in the markup of architectural drawings, making this process more efficient.

7.4 Test 4: Generating Acoustic Criteria Tables

A fourth proof of concept test was carried out using a Custom GPT model to generate a table of internal noise level and reverberation time criteria based on the types of rooms identified from architectural drawings. The objective of this test was to assess whether the model could automate the creation of acoustic criteria tables aligned with industry standards, such as those specified in AS/NZS 2107:2016.

The test was successful, demonstrating the Custom GPT's capability to accurately produce a table of acoustic criteria. After extracting room names and functions from the architectural drawings, the model correctly referenced the corresponding internal noise level and reverberation time criteria for each room type according to the standard. The resulting table provided a clear summary of the acoustic performance targets, such as maximum permissible noise levels and optimal reverberation times, tailored to each specific space.

This successful outcome highlights the potential of using Al tools like Custom GPT to streamline the process of generating acoustic documentation. Automating the creation of such criteria tables can significantly reduce the manual effort required, minimise errors, and ensure consistent adherence to recognised standards. This functionality is particularly valuable in large or complex projects where multiple spaces with varying acoustic requirements must be evaluated.

7.5 Proof of Concept Test Summary

The positive results from these tests underscore the practical benefits of integrating AI models into the workflow of acoustic consulting. By automating routine but critical tasks, such as generating acoustic criteria tables, AI can help consultants focus more on strategic decision-making and design optimisation, leading to better project outcomes and enhanced efficiency.

8 NEXT STEPS AND FUTURE DIRECTIONS

The results of the proof-of-concept tests help validate the feasibility of the proposed AI framework and guide the development of a fully customised tool for acoustic consulting. The outcomes from these tests could lead to the refinement of model selection, feature engineering, and integration strategies, with the aim of developing a robust AI tool that enhances the efficiency, accuracy, and consistency of acoustic analysis. Further research could also explore the integration of these AI models with existing software platforms used in the industry, ensuring a seamless transition from concept to practical application.

9 CONCLUSION

This paper explores a proposed framework for leveraging AI in acoustic consulting by automating the analysis of architectural drawings. Through a series of proof-of-concept tests using a Custom GPT model, the potential and limitations of AI tools in extracting relevant information, classifying room types, identifying room adjacencies, and generating acoustic criteria tables were demonstrated. While the model showed promise in tasks such as room classification and criteria generation, it faced challenges in accurately recognising all architectural features and spatial relationships.

These findings suggest that while AI has significant potential to improve efficiency, accuracy, and consistency in acoustic consulting, further development and integration with more advanced computer vision and machine learning tools are needed. Future research should focus on refining these AI techniques to handle complex architectural drawings and better support acoustic consultants in their decision-making processes, ultimately enhancing the quality and outcomes of building design projects.

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