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INTERNATIONAL ACADEMIC RESEARCH AND STUDIES IN
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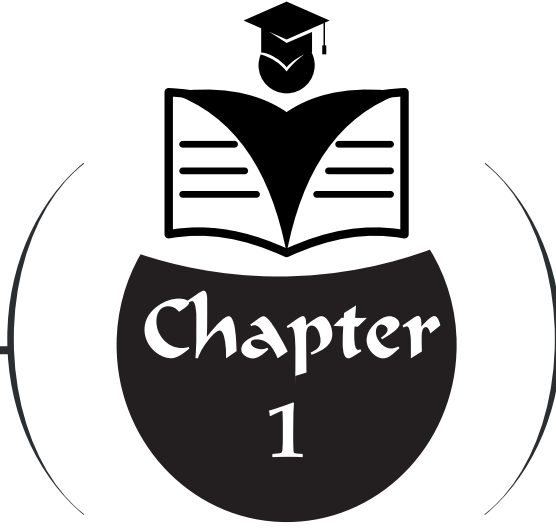
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IMPLEMENTATION OF DIGITAL ONBOARDING SUPPORTED WITH ARTIFICIAL INTELLIGENCE

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1. INTRODUCTION

Know Your Customer (KYC) refers to a procedure adopted by businesses and financial organizations to verify the identity of their clients, ensuring compliance with relevant legal standards, regulations, and obligations. It serves as the foundational step in forming and sustaining a professional relationship between a company and its customers. KYC involves gathering thorough information about clients' financial status, investment expertise, and tolerance for risk. It is considered crucial to have a clear understanding of the customer before initiating any financial transactions, particularly those involving large sums of money.

The pandemic of COVID-19 created a record-breaking boom in digital onboarding, speeding up the use of technology in banking industry. Banks and companies increasingly used online Know Your Customer (KYC) processes to meet more stringent regulations while keeping operations efficient (Lund et al., 2021). This change also impacted workforce dynamics, affecting employee well-being, engagement, and performance (Maurer, 2020). Digital Onboarding reshapes new customer acquisition and Know your Customer (KYC) practices in the banking sector in an online environment, and includes creating a new bank account in banking transactions, as well as making financial applications, increasing credit card limits and renewing passwords (SCSoft, 2025)

As a result, Know Your Customer and new customer acquisition has emerged as an important method for the banking industry as well as workforce integration, efficiency, and compliance requirements.

1.1 Explaining Digital Onboarding in Digital Banks

In the banking sector, digital onboarding refers to an automated process that grants customers access to financial products and services (Aamer & Milani, 2023). This can involve activities such as opening a bank account, applying for a loan, or registering with a digital bank or neobank.

What differentiates digital onboarding from traditional onboarding is that it is entirely conducted online. It is designed to be quick, seamless, user friendly, and secure, while still adhering to the same legal and regulatory requirements as offline processes (Karim et al., 2023).

1.1.1 What is ID Verification?

ID verification is the process of authenticating the identity of an individual or entity using documents and biometric data to prevent money laundering and financial crimes (Aamer & Milani, 2023). It is crucial for businesses, as it helps mitigate fraud, identity theft, and other related risks.

ID verification has become an essential part of contemporary online business operations. Given the growing threats in the digital space, companies must implement robust systems to confirm the legitimacy of user identities and protect sensitive information (Khare & Srivastava, 2023). By adopting effective ID verification practices, businesses can prevent fraudulent activities, ensure compliance with regulations, and strengthen both business and user security (HUB, 2024).

As businesses continue to transition their operations online, they face a growing array of cyber threats, including fraud (Qiang, 2024). Identity theft, in particular, has become a widespread online risk, where the use of unverified identities can result in the misuse of personal information, leading to significant financial losses and reputational damage.

In light of these challenges, ID verification has evolved from an optional practice to a critical necessity for businesses in the digital landscape. It acts as a vital line of defense, safeguarding secure online transactions by verifying that the individual involved in a transaction is truly who they purport to be (HUB, 2024).

1.1.2 Traditional KYC Methods

There are various methods available for verifying a user's identity online. Some of the most common methods includes;

Biometric Verification: This method utilizes unique biological characteristics of an individual, such as fingerprints, iris scans, or facial recognition. Many smartphones now use fingerprint or face recognition technology for ID verification.

Document Verification: This approach involves verifying government issued identification documents, such as passports, driver's licenses, or national identity cards, to confirm the identity of the individual.

Knowledge Based Verification: This method asks the individual for specific information that only they should know, such as their mother's maiden name or previous addresses they've lived at, to confirm their identity.

Device Authentication: This method involves verifying the device used by the individual. The device, such as a phone or computer, is authenticated through unique identifiers like the IP address or browser fingerprint.

Email Verification: Given the widespread use of email, this method is commonly used. It involves using personal credentials set up within an email account to verify the user's identity.

Phone Verification: This process typically follows a three step procedure: the customer registers their phone number, receives a one time passcode via

SMS or phone call, and submits the passcode to complete the verification (HUB, 2024).

1.2 Why Is Online Know Your Customer a Challenge for Banks?

Know Your Customer is the critical moment when a bank accepts a new customer. Unfortunately, not all individuals seeking to open an account have good intentions (Shastri & Khandelwal, 2024). Fraudsters, cybercriminals, and other malicious actors often attempt to open fraudulent bank accounts online, with the aim of laundering money, taking out loans they won't repay, or funding illegal activities.

To make matters worse, each failure to prevent bad actors from accessing banking services presents a significant compliance risk (Verma et al., 2023). The banking sector has long been under intense scrutiny by government agencies that enforce strict KYC, Fraud, and Anti-Money Laundering (AML) regulations. Banks that fail to comply face severe penalties.

This creates a dilemma for banks: On one hand, they aim to rapidly grow their customer base by offering a seamless and user friendly onboarding process (Yucer et al., 2024). On the other hand, being too lenient in the onboarding process opens the door to fraud, regulatory fines, and a tarnished business reputation (Yucer et al., 2024).

1.3 How Is Digital Onboarding Changing Banking?

Compared to traditional customer account creation in a brick and mortar bank, online digital onboarding has both pros and cons. In the pros section, you will find that digital onboarding can be faster, cheaper, and better at scaling. You can automate most of the processes with very little need for human intervention, which is why banks have built their entire business model on the practice. It's also much more convenient for customers – especially younger ones who grew up in the always-on economy (Ziden & Joo, 2020). The frictionless experience and availability 24/7 are especially attractive to Generation Z and millennials, who are more likely to use digital banking than legacy channels. Moreover, the Banking Regulation and Supervision Agency has made online transactions mandatory to open a bank account after the pandemic, which has accelerated the spread of the Digital Onboarding application. All of the above has inspired traditional banks to follow suit and increasingly move their operations online. Downsides to digital onboarding include having to create an audit trail, ensuring your tech infrastructure is robust enough, and reconsidering your risk strategy.

1.4 How to Minimize the Risk in Digital Onboarding

To reduce onboarding risks, digital banks need a multifaceted approach that combines cutting-edge technology with intelligent processes. Tools such

as **AI, machine learning**, and **automated risk scoring systems** help streamline the onboarding process while effectively minimizing the risk of fraud and reducing operational costs. Reuters (2024) reported that Visa AI-based risk scoring system blocked 80 million attempted fraud transactions, which were worth \$40 billion across the world. This is an indicator of how AI is successful in increasing fraud detection and refining verification processes.

Pre KYC checks and **data enrichment** are key strategies that allow banks to identify and filter out fraudulent users early, before they reach the more costly verification stages. By leveraging a variety of data sources—such as **IP addresses, device fingerprints**, and **email histories**—banks can create detailed digital profiles of potential customers (Qiang, 2024). This ensures that only legitimate users progress through the onboarding process, preventing fraud from entering the system at the earliest possible point.

1.5 Why importance of Know Your Customer?

Know Your Customer plays a crucial role in shaping both the customer experience and the overall security and compliance of an organization. A well executed digital onboarding process sets the stage for a positive relationship, ensuring customers know what to expect from your service (Mondal et al., 2016). If done poorly, however, it can leave a negative impression, potentially leading to churn and a damaged reputation. Research shows that acquiring a new customer is 5 to 25 times more expensive than retaining an existing one, making it essential to make the onboarding experience as seamless and welcoming as possible (Salmony, 2018; Maurer & Wright, 2020). In fact, customers who have a positive impression of the onboarding process tend to stay longer.

They are significantly less likely to abandon the service within the first 21 days compared to those who had a negative KYC experience. Companies that focus on creating a smooth user remote customer acquisition experience have also been able to increase their prices by up to 10% without facing pushback from customers. However, the onboarding process is not just about user experience—it also presents financial risks. Many businesses are legally required to prevent financial crimes such as money laundering and tax evasion. Failure to comply with these regulations can result in heavy financial penalties or even the loss of operating licenses. Consequently, organizations must implement a robust user KYC process to verify the identity of individuals. This is where KYC procedures come into play.

KYC typically involves a four step process to collect and verify customer information, which varies by jurisdiction but usually includes gathering the customer's full name, date of birth, and address. Once this basic information is collected, businesses must then verify the customer's identity. In the case of

remote customer acquisition, this typically involves submitting a government issued ID and a selfie to ensure the person is who they claim to be. While establishing a online Video call customer acquisition process is vital for regulatory compliance, it's also important to balance security with efficiency. If KYC processes are too burdensome or slow, it can cause high drop-off rates during the digital onboarding (Ziden & Joo, 2020). On the other hand, a well managed, userfriendly process not only ensures regulatory compliance but also leads to higher customer satisfaction.

Happy customers are more likely to recommend your service to others, creating a word of mouth marketing effect (Salmony, 2018). Additionally, when customers perceive the onboarding process as quick and efficient, they are more likely to pay a premium price for your service.

2. LITERATURE REVIEW

While the U.S. Bank Secrecy Act (BSA) of 1970 marked a pivotal moment in KYC's (Know Your Customer) regulatory history, it is essential to acknowledge that similar legislative efforts were underway globally. In Europe, for instance, countries like the United Kingdom and Germany introduced their own regulatory frameworks to combat rising financial crimes. The 1980s witnessed the European Economic Community (EEC) urging member states to adopt stringent KYC measures, fostering a coordinated approach to financial regulation (Mondal et al., 2016).

The inception of KYC brought about a paradigm shift in the mechanics of financial institutions. Initially, KYC practices involved manual processes, with banks and financial entities relying on paper based documentation for customer verification (Khare & Srivastava, 2023). Basic customer information, such as name, address and identification documents, formed the core of these early practices. The integration of these processes required significant investments in personnel training and infrastructure to meet the new regulatory demands.

The idea of financial institutions scrutinizing personal information raised questions about the balance between security and individual privacy. Some individuals viewed KYC as an intrusion into their financial affairs, expressing reservations about the extensive data collection required for compliance (Yucer et al., 2024). Nonetheless, the majority of the public recognized the need for KYC regulations as a safeguard against illicit activities.

In the 1990s, recognizing the need for standardized practices, the Bank of England took a pioneering step by introducing the first comprehensive KYC guidelines. This laid the groundwork for a globalized approach to KYC, emphasizing the importance of customer due diligence procedures (Goodermo-

te, 2020). Concurrently, international bodies like the Financial Action Task Force (FATF) developed recommendations that set a gold standard for KYC regulations worldwide. This period marked a shift from regional responses to a unified global effort in combating financial crimes (Mondal et al., 2016). Now, the KYC practices are more or less standardized across the world, leaving little room for regional specifics (Forbes Business Council, 2024).

2.1 Gaps in Existing Research

Although digital onboarding has been extensively researched in the areas of KYC and anti-fraud, some key gaps persist. Firstly, most research concentrates on the compliance and regulatory implications of digital onboarding, with few studies of its impact on customer trust and experience (Drozdowski et al., 2020; Hassan, 2023; Yucer et al., 2024). Secondly, although AI and machine learning are often described as revolutionary tools, empirical studies that measure their success rates in detecting fraud are rare (Islam et al., 2024). Furthermore, the moral issues involved in AI-based identity verification, such as data privacy and bias in biometric verification systems, have not been addressed well enough (Sarridis et al., 2023). Future studies need to examine these areas in order to gain a better insight into AI-facilitated digital onboarding.

3. TECHNOLOGICAL IMPLEMENTATION OF AI SUPPORTED DIGITAL ONBOARDING

While financial institutions fast tracked digitization of KYC, they have been moving towards AI-enabled onboarding technology more and more. This section addresses the technical infrastructure and implementation strategy supporting safe and successful digital onboarding. Within the scope of local authority audits of countries, it must comply with the criteria determined by the Online Video Identity Verification product (Gumus & Çekerekli, 2024). Information architecture model and data dictionary infrastructures that will provide the desired criteria must be provided. It should be easily integrated with the main systems in wide range of area such as finance sector, Payment Institutions, Insurance sector, public institutions, crypto markets, Ministry of Foreign Affairs, Transportation sector, and health sector etc.

3.1 Expected Technical Specifications for Online Video KYC

The application must be compatible with a wide variety of comprehensive mobile devices and operating systems, and continuous updates are essential for sustainability. On the Android platform, the application should be natively implemented using Java, with the necessary code being directly integrated into the screen. On the iOS platform, the application should also be natively implemented using Swift, with the ability to directly add the necessary code to the screen (Karim et al., 2023). MRZ (Machine Readable Zone) must be used to

capture both Identity card, Passport and validate customer information, and NFC (Near Field Communication) should also be used for capturing and validating customer details (Khare & Srivastava, 2023). Additionally, voice and video recordings, as well as screenshots, should be captured and stored.

Simulator support is necessary for both iOS and Android platforms. The application should support a wide range of smartphone models, both on iOS and Android. Devices must be compatible with the iOS Swift and Android Java mobile application libraries. In addition to these, cross-platform support should also be provided, ensuring ease of use for React Native and Flutter. Application libraries should be available as UI components whenever required. These libraries can be integrated into the desired screens of the main mobile application. During an online video call, it should be possible to verify both the front and back sides of a document without leaving the call. The main application should collect the photo, MRZ, and NFC data from UI components for validation and send this data to the server (Karim et al., 2023).

For iOS, support for Xcode 12 should be available. Validation processes and security should be handled on the server side (Qiang, 2024). The validation of data read via NFC, the analysis of depth and texture in artificially created photos and videos, and facial recognition should be supported. REST services should also be available to retrieve customer and process information generated on the mobile side.

3.2 Know Your Customer Application Functional Features

Know Your Customer application described focuses on leveraging advanced technologies such as NFC (Near Field Communication), MRZ, and AI-supported liveness detection for secure, efficient customer verification in mobile applications. Here's an overview of the functional features outlined for the KYC Mobile Application (SCSoft, 2025).

3.2.1 Mobile Application Features

3.2.1.1 NFC Technology: The identity information on the chip of the identity document is verified using Near Field Communication (NFC).

- The use of identity documents that feature visual security elements visible under white light, including a photo and a wet signature.
- Verification that the identity document is issued by the authorized authority and that the information on the contactless chip has not been altered.
- Ensuring that the keys on the root certificate of the identity document cannot be duplicated.
- Verification of the validity and authenticity of the data and informa-

tion contained in the presented identity document.

3.2.1.2 Machine Readable Zone (MRZ) Technology

MRZ is a special area found on chipenabled identity documents (such as passports, ID cards, visas, driver's licenses, etc.) that contains data readable by machines. MRZ technology is commonly used for fast and secure identity verification and border control processes (Karim et al., 2023). This area typically consists of a series of alphanumeric characters arranged in a specific format.

MRZ Structure and Format

MRZ typically consists of three lines, with each line containing between 30 to 44 characters. These formats are usually designed in accordance with the standards set by the International Civil Aviation Organization (ICAO). The most common formats for passports are:

- **Passport Format (TD1):** This format is usually used for ID cards and small sized passports. It consists of 3 lines.
- **Biometric Passport Format (TD2):** Found in passports containing biometric information for international travel.

Each line may include the following types of information:

- **Personal Information:** Basic data such as name, surname, date of birth, gender, etc.
- **Document Number:** The unique number of the passport or identity document.
- **National ID Number:** The national registration number of the document holder (in some countries).
- **Expiration Date and Issue Date:** The validity periods of the document.
- **Internationally Standardized Characters:** Uppercase letters, numbers, and typically control characters arranged in a specific format.

Applications of MRZ

MRZ technology is widely used in areas such as border security, airports, highway checkpoints, and consular procedures. The main areas of use for MRZ are as follows:

- **Border Control:** In passport and visa checks, MRZ allows security personnel or machines to carry out identity verification quickly and accurately.
- **Automatic Data Collection:** MRZ technology enables automatic data

collection from passports or ID cards, eliminating human error.

- **Fast Passage Systems:** MRZ is used in automatic passage systems (e.g., automatic biometric gate systems) to speed up passport reading and identity verification processes.

Technological Advancements and Future Trends

MRZ technology has become more secure and faster over time. Modern passports are equipped with more advanced security measures and biometric data. Additionally, the use of MRZ in digital formats has become compatible with smartphones and mobile devices. In the future, MRZ is expected to be integrated into broader data fields, and more advanced verification systems are likely to be implemented.

MRZ technology plays a crucial role in global travel and identity verification processes. However, with continuously evolving technologies and increasing security threats, MRZ will need to evolve. In this context, the integration of stronger encryption and biometric verification methods will be key aspects of future developments.

3.2.1.3 OCR Technology for Reading Data on Identity Documents:

- High quality front and rear photographs of the identity document are captured, ensuring that all security elements of the identity document are visible and can be analyzed during the video call. This includes enabling the required legal checks and ensuring the photographs are of suitable quality for transfer.
- The text fields on the identity document are read via OCR, while the black and white photograph and signature fields are captured.
- **Biometric Integration:** In biometric passports, the OCR is often integrated with biometric data, enhancing travel security.

3.2.1.4 Liveness Detection and Comparison with Identity Document Photos:

- The mobile application issues variable and random prompts (e.g., turning the head left or right, smiling, blinking, etc.) to measure the subject's compliance with these instructions, which is then scored.
- In the remote identification process, the biometric comparison of the face with the person's picture on the contactless chip from the identity document using near field communication (NFC) or the biometric comparison of the person's picture scanned with OCR.
- Age and gender analysis should perform to verify compatibility with the details on the identity document.

- Liveness analysis should also be performed using speech to text technology.
- The mobile application should provide visual, auditory, and written guidance to facilitate the user experience during the NFC, MRZ, and liveness detection steps of the mobile application, application submission, and video call processes.
- The guidance on these screens is expected to be designed using visual elements that enhance the user's experience.
- Video call redirection should include within the application.
- Mechanisms should establish to minimize the potential for fraud by preventing predictable situations, such as a specific person being assigned to a particular customer representative, during remote identity verification assignments.
- All data collected on the mobile application screens should be transferred to the video call screens, recorded for future review, and subjected to audit trails.

3.2.1.5 Risk Assessment Integration:

- Integration should be provided in order to compare the data obtained from the application form and identity sharing system with the risk assessment criteria of systems in industries such as banking, energy, e-money, payment institutions, crypto markets, insurance and as well as the health and insurance.
- A risk assessment should be conducted using the collected data.
- Scores from liveness detection should be reflected in the risk assessment score.
- Depending on the risk assessment results, the process can be terminated before initiating the video call if necessary.
- In cases of inappropriate behavior, fraud, forgery, or similar issues detected during the remote identity verification process, the process will be terminated.
- In case of any inappropriate behavior, approach, fraud, forgery etc. that may occur from a person during the remote identification process, the process is terminated (SCSoft, 2025).

3.2.1.6 Identity Verification Application via Video Call

The screens of the video call identity verification application should be user friendly and are expected to provide ease of use for the customer. Some features;

- The user experience should be designed in such a way that the representative can proceed step by step according to business rules within the scope of the screens.

- The design of the video call screen should be designed in accordance with the workflow and needs of companies such as those in the banking, electronic payment, payment institutions, insurance and healthcare sectors.

- Messages such as transaction completion, warnings, error messages, biometric and data comparisons, and other result based messages should be designed to be displayed in a single area from the perspective of user experience.

3.2.1.7 Customer Representative Video Call Waiting Panel

- The user experience should be designed in such a way that the representative can proceed step by step according to business rules within the scope of the screens.

- The design of the video call screen should be tailored to meet the bank's workflow and requirements.

- Messages such as transaction completion, warnings, error messages, biometric and data comparisons, and other result based messages should be designed to be displayed in a single area from the perspective of user experience.

- Queue status
- Working time
- Average call duration
- Call statistics
- Break times
- Status change buttons
- Call answering buttons
- Voice and visual notifications for calls directed to the customer representative on the dashboard screen

Customer Representative Video Call Panel

- Call management buttons
- Call termination button
- Buttons to toggle the customer representative's audio and video
- Front back camera switch button

- Flash on/off button

The photos taken should meet the following requirements and standards:

Using individual images captured from the person's movements, zoomed in and cropped, ensuring that all security features visible under white light are accurately captured at the correct angle, and ensuring that no artificial distortions are present at the transition points between sections of the identity document.

The quality should allow for clear inspection of the document.

Displaying Data Collected from the Mobile Application

- Applicant's data from the application form
- Risk assessment results
- Data from the identity sharing system
- Front and rear photos of the identity document
- Mobile device and connection information

Remote Identity Verification Data Validation and Comparison Screens

- Biometric comparison and display of the picture should be obtained through NFC and the picture should be taken during liveness detection.

- Biometric comparison and display of the picture could be obtained through OCR and the photo taken during liveness detection.

- Comparison and display of the accuracy and consistency between NFC/MRZ data and the data from the identity sharing system.

- Verification that the information on the identity document matches the data known by the bank, data obtained from the identity sharing system, and any other accessible information for identity verification purposes.

- The following checks are conducted on the identity security features (guilloche, rainbow printing, optically variable ink, hidden image, hologram, and microtext), and the results are displayed for validation.

- Verified that the information in the MRZ (Machine Readable Zone) matches the information on the identity document.

- Mandatory checks should be performed, and in the event of negative results, the representative is presented with the option to terminate the call before proceeding to the security verification screen.

3.2.3 Security Verification Screens

In the context of online video conferencing KYC procedures, it is neces-

sary to provide the following screens and workflow that will guide customer representatives step by step and ensure verifications are performed with system based controls. In cases where NFC verification cannot be completed, an additional screen will be designed to randomly verify four elements of the identity document. Along with the system's security checks on identity features, the ability to take a high

quality photo of the identity document for review, zoom in for inspection, and store the photo with audit trails should be enabled.

Identity Document Touch Test: A random and variable touch test can be performed on the security features of the identity document, including taking photos, reviewing, cropping, and saving.

The captured photo can be linked to the verification questions.

Random and Variable Questions Displayed on Screen by the Customer Representative

- The questions to be asked can be defined and managed parametrically and by category.
- Question responses can be entered as free text by category or through yes/no selections.
- Both category based selection and explanatory options should be available for question responses.
- The system will compare the entered identity document serial number with the Identity Sharing System, NFC, MRZ data to display the results. This feature should be mandatory.

HighQuality Front/Back Photos of the Identity Document

- The captured document should allow zooming and rotating for closer inspection. o The document should be viewable in both horizontal and vertical orientations.
- Zooming in and out features should be applicable to the desired area of the identity document, with focus and precision level settings.
- High quality photos of both the front and back of the identity document should be captured, reviewed, cropped, and saved.
- The process should prevent progress without meeting the defined verification criteria in the security steps.

General Information Screen at the End of the Session

A screen should be designed for the customer representative to provide information about banking services and to obtain verbal consent from the

customer regarding their acceptance as a bank customer.

- All products, services, campaigns, etc., that may be presented to the customer should be parametrically definable and manageable on this screen.

- If there are issues such as poor audio, video, connection, or lighting quality during the video call, a "call termination" status should be available for the customer representative to end the call due to technical reasons.

- In case of fraud, forgery, or fake applications detected during the video call, a call termination status should be added to allow the customer representative to end the call for related reasons. Calls terminated with this status should be transferred to the bank's blacklist, preventing the application from entering the video conferencing process again.

- If the process is deemed risky by the customer representative, the call should be sent for approval to a second representative, and a corresponding termination status should be added. This status should allow the second representative to review the full audio, video, data, logs, etc., of the mobile and video conferencing process.

- A status should be added to indicate a successful conclusion of the video call.

- A structure should be designed for the customer representative to add free form notes during the video call, with the notes logged.

- If the person terminates the session, the session should be closed on the user side, and the representative should be prompted to select the call's conclusion status, allowing for the termination of the call.

- All records in the terminated statuses should be fully accessible for historical review, including mobile and video conferencing data, audio, video, logs, etc.

3.2.2 Automatic Call Distribution (ACD)

The Automatic Call Distribution system plays a crucial role in the effective management of calls by customer representatives in the video based identity verification system. This application can be vital for institutions handling multiple video calls simultaneously. The following core features add value to the customers:

- The ability to assign calls to the representative who has been in the ready state the longest when a call arrives.

- The call (audio/video) notification should only activate for the assigned representative.

- The representative should be able to answer the assigned call by pressing the "Answer Call" button within a predefined (parametric) time.
- If the representative does not answer the call within the designated (parametric) time, the call is automatically answered, and the representative is taken to the call room.
- The customer representative logs into the system. When ACD is active, calls are automatically assigned (SCSoft, 2025).
- A call should be initiated from a mobile device during automatic assignment.
- After initiating the call, it should be terminated from the mobile side.
- The agent screen should notify when there is a missed call.

3.2.3 Supervisor/Reporting/Admin Module

The following basic features are provided for the management of the credentials to be presented together with the administrator panel (SCSoft, 2025).

- Queue Monitoring Screens
- Incoming Call Statistics (Incoming Calls, Answered Calls, Missed Calls, etc.)
- SLA Measurement Screens (Service Level, Answer Rate, Response Times, etc.)
- Customer Representative Status Screens and Statistics (Break Times, Call Durations, etc.)
- Customer Representative Workgroup Definition Management Screen (This can be used in cases with multiple video call services)
- User based Authorization Management on the Screens (For example, granting access to only reports or full access to the entire screen, etc.)
- Full Access and Review of All Records
- Each record should have a unique call ID.
- Voice Recordings
- Customer and Representative Video Recordings
- Recording of the customer representative's screen from the beginning to the end of the video call, with access to the data
- Simultaneous tracking of video call logs during the call
- Photos such as ID cards, selfies, invoices, etc.

- Free notes taken during the call
- Free notes taken by the approver
- Call closure statuses
- All records should be examined and monitored in a structure that preserves the integrity of the video call process.
- Design and updating of questions to be asked on customer representative screens, as well as the option to add or remove questions
- A screen and process design should be in place on the supervisor's screen, allowing the review of records sent for approval by customer representatives, with options for approval or rejection, adding free comments, and triggering the flow to the banking system.
- SLA measurement reports (Service Level, Answer Rate, Response Times, etc.)
- Customer Representative Statistical Reports (Break, work hours, login, logout, etc.)

3.3 The Impact of Video Calls and Livelihood Analysis on Fraudulent Transactions

The technology of video calls has become an integral part of fraud detection and prevention methods in the financial sector. With many advantages such as identity verification, behavioral analysis, dynamic authentication processes, and enhancing customer trust, banks can more effectively detect and prevent fraudulent attempts. This technology, offering real time detection capabilities, strengthens financial fraud prevention strategies and subsequently enhances customer satisfaction. The importance of video calling in combating fraud underscores the need for financial institutions to adopt and utilize this technology more widely and effectively.

In the process of monitoring fraudulent transactions, the importance of directly communicating with the real customer and confirming transactions when unusual activities are detected is undeniable. When a transaction on an compromised account is confirmed by the fraudster during a call, it can lead to financial loss as well as damage to customer and sector reputation. Video calling is the most effective way to directly communicate with the customer and verify their identity. It provides a personal and reliable communication channel for the customer, while also allowing the financial institution to evaluate the overall behavior of the person through techniques such as tone of voice, facial expressions, and speech to text, thus clarifying suspicious situations (Gumus, 2024).

Although AI-based identity verification has transformed digital onboarding, it comes with issues related to data protection, algorithmic bias, and regulatory compliance. Research has revealed that facial recognition systems can possess greater error rates for specific populations, resulting in possible biases in identity verification (Yucer et al., 2024). Also, regulatory requirements like GDPR and CCPA demand that financial institutions provide transparent AI decision making and strong data encryption practices. Tackling these issues is paramount to instilling confidence in AI-driven digital onboarding tools.

3. CONCLUSION

Know Your Customer applications provides comprehensive solutions for all types of businesses globally. The verification is highly automated and reliable. KYC is an innovative digital solution that has the potential to revolutionize the KYC process for financial institutions worldwide. By leveraging advanced technologies such as Artificial Intelligence (AI), Machine Learning (ML), and biometrics. KYC Verification provides a faster, more efficient, and more accurate verification process for financial institutions and their customers.

While KYC offers many benefits, financial institutions must also address the challenges of customer awareness, technical issues, and regulatory compliance. Financial institutions can ensure successful Digital Onboarding Verification adoption by following best practices such as developing clear policies and procedures, investing in advanced technologies, and offering customer education and technical support.

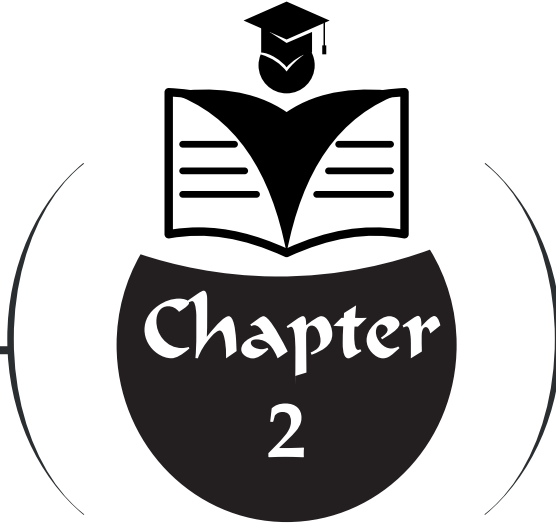
With continued digital transformation, KYC procedures will increasingly incorporate more sophisticated technologies, which will provide an efficient, seamless, and secure experience for financial institutions and customers alike. KYC products can be used in a wide range of sectors such as banking, insurance, payment institutions, e-money, crypto markets, as well as the health sector, transportation and agriculture. With the increase in use, expert processes in the insurance system can be digitized, saving time and reducing costs. The usage area of the application is not limited to these sectors, but it can be used in all areas where ID card verification is performed and its use is becoming more widespread day by day.

As the use of remote customer acquisition increases and becomes more widespread, security and fraud operations will also increase. Applications will need to work integrated with Fraud Prevention Systems and security measures will need to be increased even more. In Know Your Customer (KYC) processes, particularly within the banking sector, the necessity for supplementary security measures in response to evolving regulations will require a highly adaptive management approach. This topic could be explored in a dedicated article.

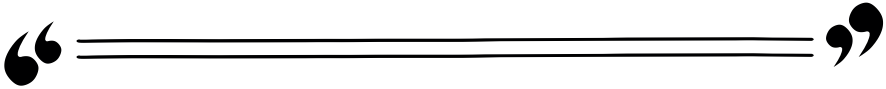
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ANALYSIS OF FACTORS AFFECTING AGRICULTURAL IRRIGATION SYSTEM SELECTION WITH FUCOM METHOD



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1. Introduction

Water resources are of critical importance for the continuity of human activities and the sustainability of ecosystems. Factors such as increasing population, industrialization, agriculture and climate change are causing serious pressure on water resources. While water resources are rapidly decreasing, the demand for water is also constantly increasing, making it necessary to use our country's existing water resources in a planned, efficient and sustainable manner to meet all needs (Çetin et al., 2010).

In the agricultural sector, which consumes a significant proportion of the world's available water resources, ensuring the efficient transportation, distribution and utilisation of water by plants is a primary responsibility of water users and farmers (Tekiner, 2020). The most significant factor in increasing the diversity and quantity of agricultural production is the availability of water (Öter & Bahar, 2018). To increase agricultural production and obtain quality products, it is essential that the water required by the plant is delivered to the root zone at the optimum time and in the appropriate amount (Davarcı & Taş, 2020). In this context, effective water management and the implementation of appropriate irrigation techniques are of paramount importance to prevent water wastage and to enhance agricultural productivity.

The successful provision of water to plants at the optimum time and in the appropriate amount is only possible with systems designed, constructed and administered using reliable data (Kırnak et al., 2013). The efficient use of water resources can be achieved by determining the most appropriate irrigation method, planning and designing the irrigation system suitable for this method according to technical requirements, installing and operating it as envisaged, monitoring and evaluating during the implementation process, and using the obtained data to eliminate possible problems (Yıldız & Yürdem, 2017).

There are many factors that play a role in the selection and effectiveness of suitable agricultural irrigation systems, including environmental, technical, economic and social factors. These factors can be listed as climate conditions, soil characteristics, water availability and quality, efficiency of irrigation method, land

topography, water requirement of plant types, investment and operating costs, energy consumption, farmers' knowledge level, water management policies, labour force and technological infrastructure. The degree of influence of these factors on irrigation system selection is different. The weights of these factors on irrigation system selection can be determined using mathematical and statistical methods. In this direction, there are studies that evaluate the factors affecting irrigation system selection using the analytical hierarchy process method, which is frequently used among multi-criteria decision-making methods (Montazar & Behbahani, 2007; Veisi et al., 2022; Yetik & Ünal, 2024).

FUCOM (Full Consistency Method) method was developed in 2018 and is one of the multi-criteria decision-making methods employed to determine factor weights. While n represents the number of factors, $n(n-1)/2$ pairwise comparisons are made in the analytical hierarchy process method, $n-1$ pairwise comparisons are made in the FUCOM method (Alkan & Durduran, 2024). FUCOM method facilitates calculation by reducing the number of pairwise comparisons. While the consistency ratio is calculated in the analytical hierarchy process method, consistency is ensured with the mathematical transitivity condition in the FUCOM method. A considerable body of research has been dedicated to the utilisation of the FUCOM method for the determination of factor weights (Aka, 2023; Akar, 2022; Alkan & Durduran, 2024; Canat & Özkan, 2025; Durmić, 2019; Ecer, 2021; Ekin & Sarul, 2022; Mercan & Can, 2023; Öztaş & Öztaş, 2023).

In this study, the factors affecting the selection of agricultural irrigation systems were analysed using the FUCOM method. To this end, the opinions of three decision makers who are experts in the field of agricultural engineering were consulted. According to the analysis results, it was determined that the most important factor in the selection of the irrigation system was water availability, while the least important factor was labour force.

2. Material and Method

To select an agricultural irrigation system that is both effective and appropriate, it is necessary to take several factors into consideration. These factors are land surface shape, soil properties, type of plant,

water availability, quality and distance, cost of water, labour and technological facilities, construction and operation costs of irrigation facilities, economic parameters, climatic characteristics (Bayramoğlu & Ağızan, 2018).

In a study conducted in Niğde province, the factors affecting the selection of irrigation system were determined as water use efficiency, system cost, plant type, technical knowledge, water availability, climate, soil type, slope and traditional habits (Yetik & Ünal, 2024) .

In another study conducted in Iran, the factors affecting the selection of irrigation system were determined as crop density, plant diseases susceptibility, crop value, land area, land slope, growing conditions, infiltration rate, irrigation water quality, irrigation water quantity, wind speed, technical support requirements, availability of skilled labour, cultural acceptability of the irrigation system, system costs, and labour skills (Montazar & Behbahani, 2007).

In this study, the factors affecting the selection of agricultural irrigation system were determined as land surface shape, soil properties, water availability, water quality, plant type, climatic characteristics, irrigation system cost, technological facilities and labour force. The explanation about these factors is given below.

- Land surface shape (F1): The slope and roughness of the land play an important role in the selection of the irrigation system.
- Soil properties (F2): The water holding capacity, permeability and salinity of the soil determine the most efficient irrigation method.
- Water availability (F3): The region's water resources are of paramount importance, as they determine the availability of water for irrigation and the sustainability of the irrigation system.
- Water quality (F4): The presence of salt, lime, and heavy metals in irrigation water is a crucial factor in the development of plants and the longevity of the irrigation system.
- Plant type (F5): The necessity for irrigation is contingent upon the specific type of plant cultivated.

- Climatic characteristics (F6): The necessity for irrigation is directly influenced by a variety of climatic factors, including temperature, rainfall, humidity and evaporation rate.
- Irrigation system cost (F7): The initial investment and operating costs of an irrigation method are a significant factor in determining farmers' preferences.
- Technological facilities (F8): Supporting irrigation systems with technologies such as automation, sensors and remote-control increase water use efficiency. However, technological possibilities depend on the investment cost and the infrastructure in the region.
- Labour force (F9): The labour required for the operation and maintenance of irrigation systems is also a pertinent consideration.

FUCOM

FUCOM was introduced to the literature in 2018 by Pamucar et al. This method, which is quite new, is one of the subjective methods used to calculate factor weights.

The advantages of this method are as follows (Mercan & Can, 2023):

- It reaches the result by making $n-1$ pairwise comparisons, where n represents the number of factors, that is, by making fewer pairwise comparisons.
- Consistency is at the forefront when making pairwise comparisons.
- It allows the calculation of factor weights in a reliable manner.

The application stages of the FUCOM method are as follows (Ecer, 2021; Pamučar et al., 2018):

Step 1: First, the factors are ranked from the most important to the least important by the decision makers. As a result of this process, the factors are ranked according to their expected weight coefficients (Equation (1)).

$$C_{j(1)} > C_{j(2)} > \dots > C_{j(k)} \quad (1)$$

The k value given in Equation (1) represents the degree of the factors. If the factors are thought to have the same importance, the "=" sign can be used instead of ">".

Step 2: The comparative priorities of the factors ranked by the decision makers are determined as $\varphi_{k/(k+1)}$ and thus the comparative priority vector of the factors is obtained (Equation (2)).

$\varphi_{k/(k+1)}$ expresses the advantage of the ranking of the factor $C_{j(k)}$ over the ranking of the factor $C_{j(k+1)}$.

$$\Phi = (\varphi_{1/2}, \varphi_{2/3}, \varphi_{3/4}, \dots, \varphi_{k/(k+1)}) \quad (2)$$

For pairwise comparison of factors, a predetermined scale, integer or decimal values can be used.

Step 3: As a result, the final weights of the factors $(w_1, w_2, \dots, w_n)^T$ are calculated. For the calculation of the weights, the following two conditions must be fulfilled:

Condition 1: The ratio of the weight coefficients of the factors is equal to the comparative priority value of the factors specified in Step 2 (Equation (3)).

$$\frac{w_k}{w_{k+1}} = \varphi_{k/(k+1)} \quad (3)$$

Condition 2: The final values of the weight coefficients obtained must comply with mathematical transitivity. That is:
 $\varphi_{k/(k+1)} \otimes \varphi_{(k+1)/(k+2)} = \varphi_{k/(k+2)}$

Also, since $\varphi_{k/(k+1)} = \frac{w_k}{w_{k+1}}$ and $\varphi_{(k+1)/(k+2)} = \frac{w_{k+1}}{w_{k+2}}$ exist, $\frac{w_k}{w_{k+1}} \otimes \frac{w_{k+1}}{w_{k+2}} = \frac{w_k}{w_{k+2}}$ is obtained. As a result, the second condition is obtained (Equation (4)).

$$\frac{w_k}{w_{k+2}} = \varphi_{k/(k+1)} \otimes \varphi_{(k+1)/(k+2)} \quad (4)$$

When conditions 1 and 2 are met, full consistency is achieved. In other words, when these conditions are met, the deviation from full

consistency (DFC) value is minimum. The DFC value for the final values of the weight coefficients is $\chi = 0$.

Finally, to calculate the final values of the factor weights, the linear programming model given in Equation (5) must be solved.

$$\min \chi$$
$$\left\{ \begin{array}{l} \left| \frac{w_{j(k)}}{w_{j(k+1)}} - \varphi_{k/(k+1)} \right| \leq \chi, \forall j \\ \left| \frac{w_{j(k)}}{w_{j(k+2)}} - \varphi_{k/(k+1)} \otimes \varphi_{(k+1)/(k+2)} \right| \leq \chi, \forall j \\ \sum_{j=1}^n w_j = 1 \geq 0, \forall j \end{array} \right. \quad (5)$$

By solving this model, the final weights of the factors $(w_1, w_2, \dots, w_n)^T$ and DFC (χ) values are calculated.

3. Result

To determine the degree of influence of the factors affecting the selection of the appropriate agricultural irrigation system, opinions were obtained from three decision makers who are experts in agricultural engineering. The weights of these factors were determined using the FUCOM method. In this context, decision makers were asked to rank the factors from largest to smallest in terms of their importance in the first stage. In the second stage, they were asked to evaluate the importance of the most important factor compared to other factors on a scale of 1-9.

The evaluation of the factors by the decision maker-1 is given in Tables 1.

Table 1. Evaluations of decision maker-1

Ranking of Factors: F3>F2>F6>F4>F5>F1>F7>F8>F9								
Importance level of F3 factor compared to other factors	F2	F6	F4	F5	F1	F7	F8	F9
	1.5	2	2.5	4	5	6	7	9

According to decision maker-1, the most important factor is water availability (F3), and the least important factor is labour (F9). Other factors are listed according to their importance as soil properties (F2),

climatic characteristics (F6), water quality (F4), plant type (F5), land surface shape (F1), irrigation system cost (F7) and technological facilities (F8).

The evaluation of the factors by the decision maker-2 is given in Tables 2.

Table 2. Evaluations of decision maker-2

Ranking of Factors: F2>F3>F4>F6>F1>F5>F7>F8>F9								
Importance level of F2 factor compared to other factors	F3	F4	F6	F1	F5	F7	F8	F9
	1.2	1.8	2	2.4	3	5	6	8

According to decision maker-2, the most important factor is soil properties (F2), while the least important factor is labour force (F9). Other factors are listed according to their importance as water availability (F3), water quality (F4), climatic characteristics (F6), land surface shape (F1), plant type (F5), irrigation system cost (F7) and technological facilities (F8).

The evaluation of the factors by the decision maker-3 is given in Tables 3.

Table 3. Evaluations of decision maker-3

Ranking of Factors: F4>F3>F6>F2>F1>F5>F8>F7>F9								
Importance level of F4 factor compared to other factors	F3	F6	F2	F1	F5	F8	F7	F9
	1.3	2	2.5	3	4	4.5	5	8

According to decision maker-3, the most important factor is water quality (F4), while the least important factor is labour force (F9). Other factors are listed according to their importance as water availability (F3), climatic characteristics (F6), soil properties (F2), land surface shape (F1), plant type (F5), technological facilities (F8) and irrigation system cost (F7).

The weights of the factors evaluated by the decision makers according to the 1-9 scale were calculated by the FUCOM method. The geometric mean was used to determine the mean value of the weights calculated separately for each decision maker. This is to overcome the problem that the arithmetic mean is affected by extreme values. Since the sum

of the average weight values obtained by geometric mean is not 1, the weights are normalized.

The factor weights obtained are presented in Table 4.

Table 4. Factors weights

Factors	Decision Maker-1	Decision Maker-2	Decision Maker-3	Average Weights	Ranking
Land surface shape	0.058	0.101	0.088	0.082	5
Soil properties	0.194	0.242	0.105	0.175	2
Water availability	0.291	0.202	0.202	0.235	1
Water quality	0.116	0.134	0.263	0.165	3
Plant type	0.073	0.081	0.066	0.075	6
Climatic characteristics	0.145	0.121	0.132	0.136	4
Irrigation system cost	0.048	0.048	0.053	0.051	7
Technological facilities	0.042	0.040	0.058	0.047	8
Labour force	0.032	0.030	0.033	0.033	9

The graph related to the ranking of the factors according to their weights is given in Figure 1.

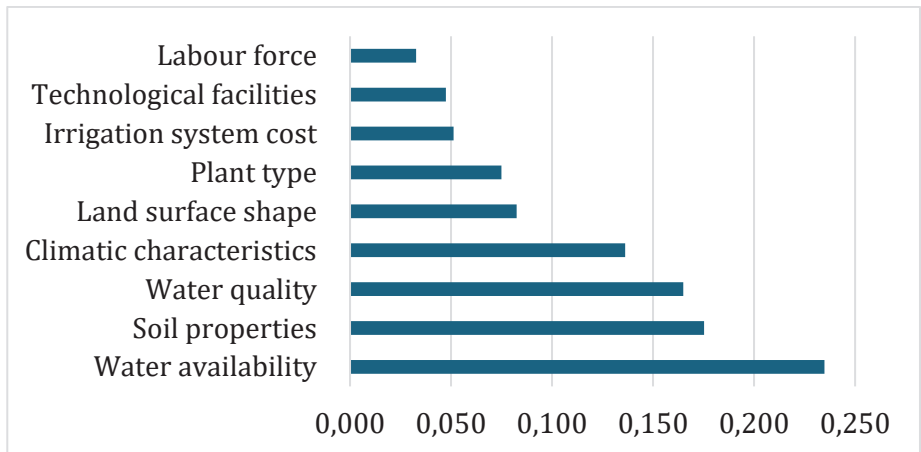


Figure 1. Ranking of factors according to their weights

When the factor weights obtained according to decision maker-1 are examined, the weight percentages according to their importance levels are as follows: water availability (29.1%), soil properties (19.4%),

climatic characteristics (14.5%), water quality (11.6%), plant type (7.3%), land surface shape (5.8%), irrigation system cost (4.8%), technological facilities (4.2%), and labour force (13.4%),

When the factor weights obtained according to decision maker-2 are examined, the weight percentages according to their importance levels are as follows: soil properties (24.2%), water availability (20.2%), water quality (11.6%), climatic characteristics (12.1%), land surface shape (10.1%), plant type (8.1%), irrigation system cost (4.8%), technological facilities (4.0%), and labour force (3.0%).

When the factor weights obtained according to decision maker-3 are examined, the weight percentages according to their importance levels are as follows: water quality (26.3%), water availability (20.2%), climatic characteristics (13.2%), soil properties (10.5%), land surface shape (8.8%), plant type (6.6%), technological facilities (5.8%), irrigation system cost (5.3%), and labour force (3.3%).

The factor weights obtained in line with the opinions of the three decision makers were normalised by taking the geometric mean. Thus, average weights were obtained. When these weights were analysed, the most important factor affecting the choice of agricultural irrigation system was water availability with 23.5%. This factor is followed by soil characteristics (17.5%), water quality (16.5%), climatic characteristics (13.6%), land surface shape (8.2%), plant type (7.5%), irrigation system cost (5.1%) and technological facilities (4.7%) in order of importance. The least important factor was labour force with 3.3%.

4. Conclusion

The factors that are effective in the selection of agricultural irrigation systems are of great importance in terms of efficient use of water, agricultural productivity and sustainability. Water availability stands out as one of the most critical factors and is decisive in terms of the sustainability of the irrigation system. Soil properties are another important element to be considered in terms of water retention capacity and permeability. Water quality should be evaluated in terms of salinity and chemical components, affecting the long-term efficiency of irrigation systems. In addition, climatic conditions and land surface shape are among the determining factors in terms of the applicability

of the system. Plant type should be taken into consideration in system selection since each plant has different water needs. While economic and technological factors are important in terms of investment costs and the applicability of modern irrigation techniques, the labour force factor should be evaluated due to its impact on the operation and maintenance processes of the system.

This study utilised the FUCOM method to conduct analyses, thereby identifying the most significant factor in system selection. The analysis revealed that water availability (0.235) emerged as the predominant factor, followed by soil characteristics (0.175), water quality (0.165), and climate characteristics (0.136). Land surface shape (0.082) and plant type (0.075) were also identified as contributing factors. The cost of the irrigation system (0.051) and technological possibilities (0.047) were identified as medium-importance factors, while the labour factor was assigned the lowest weight of .The findings of this study demonstrate that the adequacy of water resources and soil-water relations are the most critical elements in the selection of the irrigation system, and also show that economic and technical factors should not be ignored.

Agricultural irrigation systems play a critical role in ensuring the continuity of agricultural production by ensuring efficient and sustainable management of water. Global climate change and the gradual depletion of water resources have made the use of modern irrigation techniques mandatory. Modern irrigation methods prevent water waste and deliver the water needed by plants directly to the root zone, thus increasing water use efficiency. In addition, the application of correct irrigation techniques reduces soil erosion, contributes to the preservation of plant nutrients and significantly contributes to food security by increasing agricultural productivity. Therefore, the use of effective irrigation systems is of great importance in the dissemination of sustainable agricultural practices.

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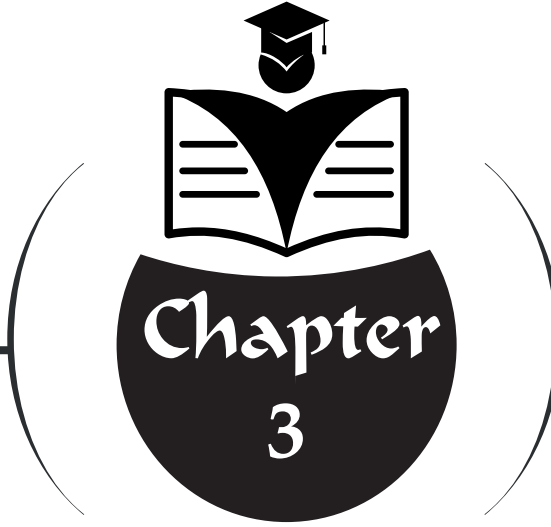
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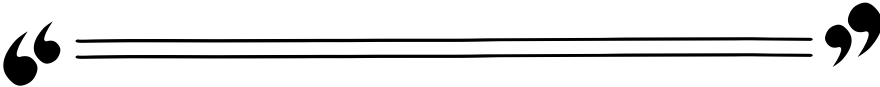
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ASSESSMENT OF TÜRKİYE'S CRITICAL RAW MATERIALS STRATEGY IN LIGHT OF THE EU'S CRITICAL RAW MATERIALS ACT



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1. Introduction

Global population growth, economic expansion in developing countries, advancements in manufacturing production technologies, and shifts in national policies have all contributed to a growing demand for non-energy mineral raw materials in recent years—both in terms of total quantity and the diversity of minerals used (<https://www.ituvakif.org.tr>).

Today, developing countries face challenges in accessing and processing the technologies and raw materials used especially in the manufacturing industry, while developed countries struggle to import the raw materials that are either unavailable or insufficient within their own borders to further strengthen their economies. The increased demand for raw materials driven by countries experiencing rapid economic growth, China's export restrictions on Rare Earth Elements, and regional cold/hot conflicts have led to “physical supply” issues in raw materials provided by certain countries—issues that go beyond simple price competition.

The world's leading economic and technological power centers are showing increasing interest in critical minerals required for the transition to clean energy. For example, the demand for minerals such as rare earth elements for catalysts and high-performance permanent magnets, lithium for batteries, and aluminum for packaging, among others, is expected to continue rising rapidly. Therefore, developed countries such as the USA, EU, and China have already prepared critical mineral strategies for the next 20, 50, even 100 years. These strategic plans detail the policies regarding the exploration of these minerals around the world, their extraction, and the establishment of supply chains. The European Union, for example, defined its strategy up to 2050 with the critical raw materials action plan it prepared in the early 2000s.

Strategic minerals are generally those that are indispensable for meeting a country's military, industrial, and essential needs, and which are available in limited quantities. These minerals are of great importance in terms of national security policies and economic independence. For example, rare earth elements are of strategic importance in many fields—from advanced defense technologies to energy storage systems. If a country is a leading producer of such minerals, these resources are considered strategic (Moss, 2013).

Critical minerals are economically significant resources used in modern technologies and energy systems, with a high risk of supply chain disruptions. Each country, based on its natural resources and in line with its transition to green energy and the development of its civil and military technologies, determines for itself which minerals are “strategic” and which are “critical.” However, due to the rapid pace of technological advancement, countries must frequently update their lists of critical or strategic minerals (Şen, 2023).

According to the Union of Chambers of Turkish Engineers and Architects (TMMOB) Chamber of Geological Engineers, if a country can supply a particular mineral from its own resources and holds a significant position in its trade, that mineral is considered a “strategic mineral” for that country. For instance, since Turkey holds over 60% of the world’s boron reserves, boron is a strategic mineral for Turkey. In other words, when assessing the potential economic contribution of a mineral alongside the projected supply risk, some “Priority Raw Materials for Supply” are relatively more important than others and are therefore considered “Critical Raw Materials.” Among these critical materials, those that could jeopardize a country’s economic and national defense security are classified as “Strategic Raw Materials.” If a country must import a particular mineral, then it is considered a “critical mineral” for that country.

2. European Union Strategic and Critical Raw Materials Policy

There are many factors—both positive and negative—that influence whether a mineral or group of minerals is classified under the term “ore.” Some of these are natural, i.e., geological, while others are variable and influenced by economic, social, and political systems.

Key geological factors include ore reserve and grade, chemical composition, mineralogy and internal structure of the ore, and the location of the deposit. Variable factors include technical considerations (such as mining, beneficiation, and industrial accessibility), economic factors (supply-demand dynamics), and political influences. Even if ore availability exists, proper extraction methods, along with economic and political systems, play a crucial role in today’s mineral utilization.

Looking at the international strategy, the European Union (EU) has, in recent years, developed a comprehensive policy on critical and strategic minerals. The primary goal of these policies is to ensure the EU’s supply security and reduce dependency on external sources, while achieving its green and digital transformation objectives.

According to the Critical Raw Materials Act (CRMA, 2023) issued by the European Commission in March 2023, the main objectives are: Establishing a list of strategic raw materials, Reducing supply chain risks, Increasing domestic EU production, processing, and recycling, Reducing import dependency (especially on China), Ensuring the EU’s strategic autonomy. In its 2030 targets, the EU has planned to meet: 10% of its annual consumption through domestic mining, 40% through processing within the EU, and 15% through recycling.

According to the 2023 Critical Raw Materials List, key critical raw materials identified by the EU include:

Lithium, Cobalt, Nickel, Graphite, Rare Earth Elements (REEs), Antimony, Magnesium, Tungsten, Gallium, Germanium, Boron, Scandium, Helium, and Vanadium.

The Strategic Raw Materials List consists of 17 raw materials that are of key importance for energy transition, defense, aerospace, and digital technologies. The materials in this list are presented in Table 1, along with their areas of application.

Table 1. European Union Strategic Raw Materials List (Critical Raw Materials List – 2023)

Strategic Raw Material	Key Applications
Lithium	Batteries, e-mobility
Cobalt	Batteries
Nickel	Batteries, alloys
Rare Earth Elements	Magnets, turbines, defense systems
Gallium	Semiconductors, LEDs
Germanium	Fiber optics, infrared optics
Scandium	Alloys, aerospace technologies
Magnesium	Lightweight metal alloys
Silicon metal	Solar panels, semiconductors

To avoid dependency on a single country for raw materials, the **EU is taking the following actions:**

- Establishing partnerships with countries such as **Canada, Australia, Namibia, Kazakhstan, Argentina, and Zambia,**
- Financing mining infrastructure investments through the **EU-Global Gateway** program,
- Emphasizing **responsible mining** and **environmental standards.**

As part of its **Reprocessing and Recycling Strategy**, the EU promotes the recovery of strategic minerals from secondary raw material sources (such as waste and electronic scrap) and encourages the concept of **urban mining.**

The EU’s critical and strategic raw materials policy is based on the principles of **supply security and diversification, sustainable geopolitical independence, and ethical, circular-economy-based mining.**

The **opportunities and risks** that the EU’s critical and strategic raw materials policies pose for **Türkiye** are presented in **Table 2**.

Table 2. Assessment of the European Union’s Critical and Strategic Raw Materials Policies from Turkey’s Perspective

Category	Opportunities	Risks
Supply Chain	Turkey can serve as an alternative supplier to the EU due to its geographical proximity and logistical advantages.	The EU’s increasing domestic production and recycling capacity may reduce Turkey’s export market share.
Raw Material Potential	Turkey has strong potential in strategic minerals such as boron, chrome, feldspar, barite, and fluorite.	However, the lack of reserves in many critical minerals (e.g., lithium, cobalt, REEs) poses a significant limitation.
Geopolitical Position	Turkey could act as an alternative supply corridor in the EU’s efforts to reduce dependence on China.	Yet, geopolitical tensions with major actors such as China and Russia may expose Turkey to strategic risks.
Technological Partnership	EU–Turkey cooperation in technology transfer and joint R&D initiatives could be enhanced.	Turkey’s limited refining and advanced processing capacity constrains its ability to participate in high value-added production.

In this context, Turkey must formulate its own policy framework with regard to the key dimensions of category, opportunities, and risks.

3. Türkiye’s Mineral Potential, Strategic and Critical Raw Material Policy

Türkiye, which holds a significant share in global trade, is home to 70 out of 90 types of minerals. In 2023, the mining sector contributed substantially to the national economy with an export value of 5.748 billion USD. The total economic size of the sector reached 270 billion Turkish Liras, accounting for 1% of the Gross Domestic Product (GDP), and providing direct employment to 146,000 people (MAPEG, 2024). Within the framework of the Medium-Term Program (2025–2027), the primary objective is defined as the development of Türkiye’s Critical and Strategic Raw Materials Strategy to enhance strategic raw material supply security.

According to the report published by the Ministry of Energy and Natural Resources of the Republic of Türkiye in 2025, “Critical and strategic mineral studies carried out by many developed countries and unions such as the United States and the European Union—important players on both the supply and demand sides—are shedding light on the formulation of short- and medium-term natural resource policies. These studies evaluate countries’ mineral products, starting from the quantity of resources to reserve and production values, and assess their import and export situations. Through this, parameters such as supply risk, economic importance, and import dependency for mineral products will be revealed with quantitative data, serving as a fundamental step in shaping natural resource policies.”

According to the Strategic Minerals Report, strategic minerals are those of fundamental importance to national security and economic prosperity, whose supply may be restricted due to internal or external factors. As a first step, candidate minerals found in Türkiye were identified, and criticality scores were calculated for 37 minerals using specific assessment data. Based on these scores, it was concluded that 10 out of the 26 strategic minerals also qualify as critical minerals, and a corresponding table was prepared (Table 3).

Table 3. Strategic Mineral List (Türkiye Strategic and Critical Minerals Report, 2025)

Mineral Name	Application Area
Hafnium	Turbine engine superalloys
Ytterbium	Laser applications
Yttrium	Turbine engine superalloys and laser applications
Cobalt	Turbine engine superalloys and steel alloys
Chromium	Steel and other alloys
Lanthanum	Turbine engine superalloys
Molybdenum	Steel and other alloys
Neodymium	Laser applications
Uranium	Energy source and military applications
Rhenium	Defense industry superalloy development projects
Ruthenium	Defense industry superalloy development projects
Nickel	Steel and other alloys
Niobium	Turbine engine superalloys and steel alloys
Cerium	Turbine engine superalloys
Tantalum	Turbine engine superalloys
Titanium	Steel and other alloys
Tungsten	Steel and other alloys
Vanadium	Steel and other alloys
Zirconium	Steel and other alloys
Aluminum	Steel and other alloys
Magnesium	Steel and other alloys
Zinc	Steel and other alloys

Mineral Name	Application Area
Silicon	Steel and other alloys
Iron	Steel and other alloys
Manganese	Steel and other alloys
Carbon	Steel and other alloys

*Note: Minerals highlighted in bold are classified as both **critical** and **strategic** for Türkiye.*

The Türkiye 2025 Strategic and Critical Minerals Report is a preliminary 21-page document that lacks detailed methodological explanations. It is anticipated that future versions will include comprehensive grading criteria, weighting factors, and the underlying datasets used for evaluation. This would enhance the report’s utility in shaping more effective national mineral strategies and policy frameworks. The elements included in the list are characterized by either a high supply risk—which may lead to significant economic disruptions or supply chain vulnerabilities in the event of major price fluctuations—or by their fundamental role in national security and economic well-being, with the potential for supply constraints due to internal or external factors (*Türkiye Strategic and Critical Minerals Report, 2025*).

Given the dynamic nature of global strategic priorities, the composition of this list is expected to evolve on an annual basis.

According to the Republic of Türkiye Ministry of Energy and Natural Resources, minerals with a criticality score of 16 or above are classified as “High-Priority Critical Minerals.” This group includes lithium, silver, titanium, iron, manganese, zinc, copper, and aluminum. Minerals with a criticality score between 10 and 16 are designated as “Significant Critical Minerals,” and comprise nickel, rare earth elements (REEs), coal, palladium, cobalt, bismuth, arsenic, molybdenum, gallium, lead, cadmium, indium, germanium, niobium, tin, mercury, antimony, barite, and graphite. Minerals with a score below 10 are classified as “Potential Critical Minerals,” which include beryllium, fluor spar (fluorite), chromium, boron, platinum, magnesite, feldspar, kaolin, trona, and bentonite.

The maximum criticality score, considering weighted factors, is 35. Minerals with strong national reserves and substantial export performance and market share have been identified as critical, even in cases where external supply dependency may be limited.

In calculating criticality scores, multiple variables were considered, including foreign trade statistics, market dynamics, and political stability. Given the complexity and fluidity of these indicators, it is evident that the list

must be revised periodically—on a monthly or annual basis—to remain current and effective.

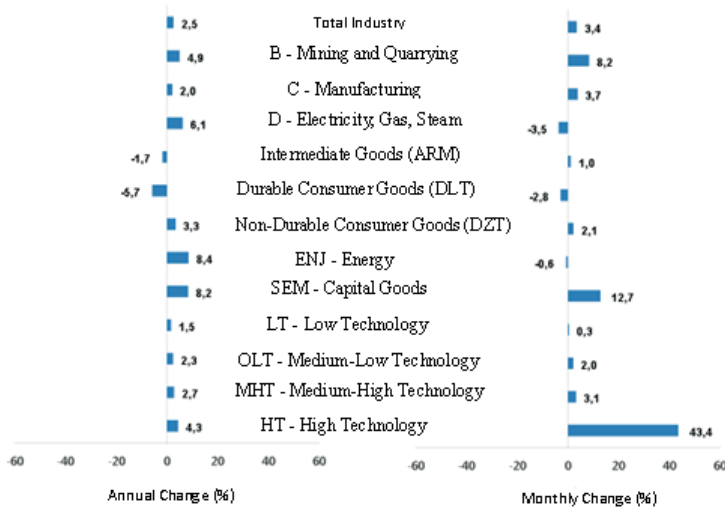
Due to its location within a geologically diverse belt, Türkiye ranks among the world’s richest countries in terms of mineral diversity (<https://www.sbb.gov.tr>). Hosting 70 out of the 90 globally traded minerals, Türkiye is ranked 10th globally in terms of mineral diversity. Türkiye possesses 2.2% of the world’s industrial raw material reserves, 1% of coal reserves, 0.8% of geothermal energy potential, and 0.4% of metallic mineral reserves (<https://enerji.gov.tr>). To better assess the role of the mining sector in the national economy, its contribution to the Gross Domestic Product (GDP) must be considered. As of 2023, the mining sector contributed 270 billion Turkish Lira, corresponding to 1.02% of GDP. Moreover, according to the March 2025 industrial production index, the mining and quarrying sector index increased by 4.9% compared to the same month of the previous year (Table 4).

Table 4. Industrial Production Index Growth Rates (%), March 2025 (TÜİK, 2025) (A) (B)

(A)

Sector	Annual Change (%)	Monthly Change (%)
Total Industry	2.5	3.4
B - Mining and Quarrying	4.9	8.2
C - Manufacturing	2.0	3.7
D - Electricity, Gas, Steam	6.1	-3.5
Intermediate Goods (ARM)	-1.7	1.0
Durable Consumer Goods (DLT)	-5.7	-2.8
Non-Durable Consumer Goods (DZT)	3.3	2.1
ENJ - Energy	8.4	-0.6
SEM - Capital Goods	8.2	12.7
LT - Low Technology	1.5	0.3
OLT - Medium-Low Technology	2.3	2.0
MHT - Medium-High Technology	2.7	3.1
HT - High Technology	4.3	43.4

(B)



Mining activities in Türkiye are governed within the framework of an integrated management system and the principles of sustainable development, forming a core component of national policy. In this context, key objectives include:

- Improving the investment climate in the mining sector,
- Enhancing domestic exploration efforts to assess the potential of mineral, geothermal, petroleum, and natural gas resources,
- Increasing value-added through the processing of raw materials into intermediate and final products,
- Ensuring raw material supply security, and
- Reducing foreign dependency on strategic resources.

These elements collectively aim to foster a more resilient, efficient, and self-reliant extractive industry aligned with long-term national development goals.

5. Conclusions

Given its position within a geologically diverse belt, Türkiye ranks among the world's most mineral-rich countries in terms of mineral diversity. As of 2025, the country has compiled an official list of critical and strategic raw materials, identifying 37 minerals as holding critical status. Among them, 8 minerals have been designated as "High-Priority Critical Minerals." These in-

clude lithium, silver, titanium, iron, aluminum, manganese, zinc, and copper.

According to the Republic of Türkiye Ministry of Energy and Natural Resources, minerals with a criticality score of 16 and above are classified as *High-Priority Critical Minerals*. The score-based classification system also defines:

- 19 minerals with scores between 10 and 16 as *Significant Critical Minerals*, including nickel, rare earth elements, coal, palladium, cobalt, bismuth, arsenic, molybdenum, gallium, lead, cadmium, indium, germanium, niobium, tin, mercury, antimony, barite, and graphite.
- Minerals with scores below 10 are categorized as *Potential Critical Minerals*, which include beryllium, fluorspar (fluorite), chromium, boron, platinum, magnesite, feldspar, kaolin, trona, and bentonite.

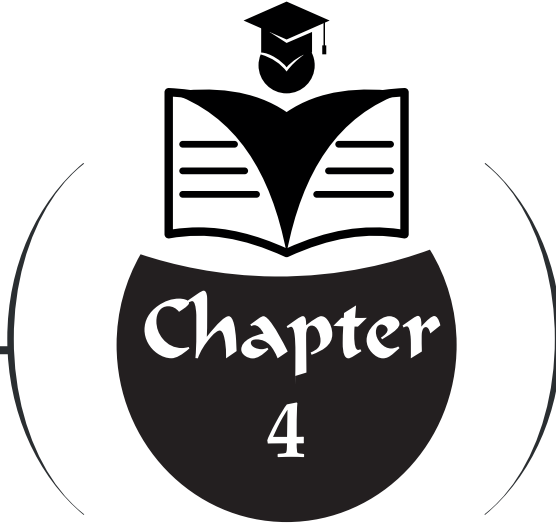
For shaping the future of Türkiye's mineral policies, it is essential that such evaluations be made more detailed, data-driven, and sustainable. The European Union's approach—emphasizing supply chain security, strategic stock planning, production incentives, and raw material strategies—serves as a model for industrial competitiveness and long-term strategic planning. Türkiye is expected to develop a comprehensive and adaptive critical raw materials strategy in alignment with these principles.

Acknowledgments

The author would like to express sincere gratitude to the Ministry of Energy and Natural Resources of the Republic of Türkiye and the General Directorate of Mining and Petroleum Affairs (MAPEG) for providing access to official datasets and publications that form the basis of this study. Special thanks are also extended to the Presidency of Strategy and Budget for their comprehensive sectoral reports that have guided the contextual analysis. This work also benefited from insights gathered from the Critical Raw Materials Act (2023) published by the European Commission, which provided a comparative framework for evaluating Türkiye's strategic positioning in raw material policy. The author acknowledges the support of colleagues and reviewers who provided valuable feedback during the development of this manuscript.

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AI-DRIVEN RISK MANAGEMENT IN CONSTRUCTION: ENHANCING SAFETY, PREDICTIVE ANALYTICS, AND PROJECT EFFICIENCY

“=====”

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1. Introduction

The construction industry, characterized by its complex and large-scale projects, is inherently exposed to a wide range of risks that can significantly jeopardize project success. These risks, which include safety hazards, budget overruns, and schedule delays, are further compounded by the involvement of multiple stakeholders and the necessity for precise coordination [1]. Traditionally, construction risk management has relied heavily on expert judgment, historical data, and manual assessments [2]. While these methods have proven useful in certain situations, they often struggle to adapt to the rapidly changing conditions of modern large-scale projects. As the scope and complexity of these projects increase, the limitations of these static, often reactive, approaches become more apparent.

In recent years, the integration of artificial intelligence (AI) into construction project management has emerged as a promising solution to address these challenges. AI introduces dynamic, real-time, data-driven systems that enhance the prediction and mitigation of risks through advanced algorithms such as machine learning (ML), deep learning (DL), and Monte Carlo simulations. These AI technologies enable the processing of vast and complex datasets, allowing for greater accuracy in predicting risks such as accidents, supply chain disruptions, and delays—areas where traditional risk management approaches have often fallen short [3,4].

1.1 Research Gap and Problem Statement

Despite the promising advancements in AI-driven risk management, significant challenges remain that hinder its widespread adoption in the construction industry. Chief among these challenges is the limited understanding of AI's full potential, particularly its ability to integrate with real-time risk monitoring systems and sustainability frameworks. For instance, AI-driven technologies are revolutionizing how organizations approach health and safety, offering predictive insights, real-time monitoring, and risk mitigation strategies that not only minimize accidents and hazards but also pave the way for a more proactive and responsive approach to safeguarding the workforce [5]. Moreover, the high initial costs associated with AI implementation, combined with the industry's general lack of technological expertise, present substantial barriers—particularly for small and medium-sized enterprises (SMEs). A systematic review identified that the lack of knowledge, costs, and inadequate infrastructure are perceived as the most common barriers to AI adoption in SMEs, addressing social, economic, and technological aspects in particular [6]. Furthermore, data security concerns are increasingly critical as construction projects rely more heavily on sensitive information shared across multiple stakeholders. AI adoption barriers in SMEs also include con-

cerns about data security and privacy, which need to be addressed to facilitate smoother and more successful AI adoption [7].

1.2 Objectives and Research Questions

This study aims to address these challenges by investigating the integration of AI-based risk management in large-scale construction projects. Specifically, the study seeks to identify key challenges, potential solutions, and future directions for AI adoption, with a focus on the following research questions:

1. How can AI-driven models improve risk mitigation in large-scale construction projects, particularly in terms of predictive accuracy and real-time data processing?
2. What are the financial and technological barriers to AI adoption in the construction industry, and how can these be mitigated to enable broader industry integration, especially for SMEs?
3. What role can AI play in promoting sustainability in construction, and how can its integration with the Internet of Things (IoT) enhance real-time risk monitoring and project efficiency?

1.3 Significance of Study

The significance of this study lies in its contribution to understanding how AI can transform risk management in the construction industry. By incorporating recent case studies from large-scale projects such as Skanska's AI-driven safety management system and Turner Construction's AI-powered crane optimization platform, this research demonstrates the practical applications and tangible benefits of AI. Moreover, the study identifies future research opportunities that explore the integration of AI with IoT and sustainability frameworks, addressing the growing demand for more efficient and eco-friendly construction practices [8].

2. Background and Literature Review

2.1 AI in Construction Project Management

The integration of artificial intelligence (AI) into the construction industry has grown significantly over the past decade, driven in part by the increasing complexity of large-scale projects [9]. Traditional project management approaches, which often rely on expert judgment and historical data, have proven insufficient in dynamic environments that demand real-time data processing and rapid decision-making [10]. To address these limitations, AI technologies such as machine learning (ML), deep learning (DL), and predictive analytics have been introduced into construction project management, enabling more accurate and efficient decision-making processes [11].

One prominent application of AI in construction is its use in cost estimation and project scheduling. By analyzing large datasets derived from previous projects, machine learning algorithms can predict potential cost overruns and delays with significantly greater accuracy compared to conventional methods. For example, [12] conducted a systematic review demonstrating the effectiveness of machine learning techniques in construction cost estimation, highlighting their superiority over traditional approaches. Similarly, [13] explored the application of machine learning in cost estimation for building projects, emphasizing its potential to improve both accuracy and operational efficiency in project management.

In addition to cost estimation, AI technologies contribute to optimizing resource allocation and enhancing decision-making processes. [14] examined the application of artificial intelligence in construction project management, emphasizing how AI systems streamline resource management and improve project outcomes through data-driven strategies.

The benefits of AI-based systems in project management are evident in Figure 1, which compares the accuracy of cost predictions generated by traditional methods with those achieved through AI-based approaches.

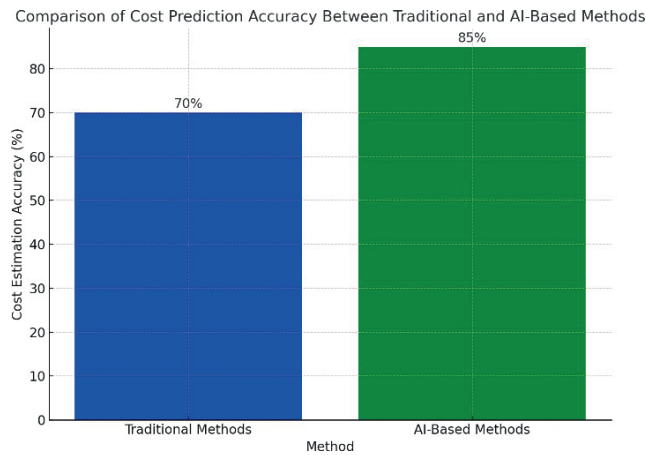


Figure 1. Comparison of Cost Prediction Accuracy Between Traditional and AI-Based Methods [15].

The figure illustrates the substantial improvement in cost estimation accuracy achieved through AI-based systems, particularly those employing machine learning techniques. By leveraging extensive datasets and identifying risk factors that traditional methods often overlook, AI offers a more reliable and effective approach to managing construction project costs. These advancements underscore the transformative potential of AI technologies in addressing the challenges of modern construction project management, ultimately enhancing efficiency and project performance [16].

Dr Öğretim Üyesi, Gaziantep İslam Bilim ve Teknoloji Üniversitesi, Mühendislik ve Doğa Bilimleri Fakültesi, İnşaat Mühendisliği, Gaziantep, osman.hansu@gibtu.edu.tr, ORCID: orcid.org/0000-0003-1638-4304 Traditional risk management practices in construction have often depended on qualitative methods and expert judgments, which can introduce subjectivity and inconsistencies across projects [17]. In contrast, artificial intelligence (AI) provides a data-driven approach that significantly enhances the accuracy of risk prediction [18]. By employing advanced algorithms such as support vector machines (SVM), random forests, and deep learning, AI systems can identify risks associated with safety, environmental hazards, and supply chain disruptions more effectively [19]. [2] highlight the transformative role of AI in improving risk management practices, noting its potential to reduce uncertainty and enhance decision-making within construction projects.

One key application of AI in construction risk management is the use of Monte Carlo simulations, which are widely utilized to model uncertainty by simulating a range of potential scenarios [20]. When integrated with AI technologies, Monte Carlo models produce more precise risk predictions by incorporating real-time data and predictive analytics [21]. This integration allows project managers to develop proactive mitigation strategies tailored to evolving risks [22]. [23] developed a framework that combines Monte Carlo simulation-based modeling with decision-makers' risk attitudes and uncertainties, further advancing the accuracy and applicability of these methods in construction risk assessment.

The advantages of AI-enhanced Monte Carlo simulations are illustrated in Figure 2, which compares the accuracy of traditional Monte Carlo models with AI-enhanced versions.

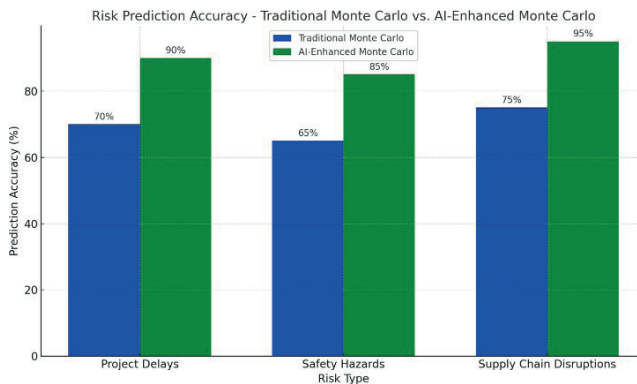


Figure 2. Risk Prediction Accuracy - Traditional Monte Carlo vs. AI-Enhanced Monte Carlo [23].

This comparison demonstrates that AI-enhanced Monte Carlo models outperform traditional simulations by incorporating real-time data and advanced predictive capabilities [24]. The increased accuracy achieved through this approach is particularly critical for large-scale construction projects, where risks are dynamic and require continuous monitoring and mitigation [25]. These findings underscore the importance of integrating AI technologies into traditional risk management practices to enhance the reliability and effectiveness of construction project planning and execution [22].

2.3 AI and Supply Chain Optimization

Supply chain management in the construction industry is inherently complex and represents a significant source of project risk, particularly in large-scale infrastructure projects [26]. Delays in material deliveries, labor shortages, and transportation issues can result in costly setbacks that compromise project timelines and budgets. The integration of artificial intelligence (AI) into supply chain management has emerged as a transformative approach to mitigating such risks [27]. AI-driven platforms leverage predictive analytics to identify potential disruptions before they occur, enabling project managers to take proactive measures to minimize delays and inefficiencies [28].

One example of AI's application in this domain is Skanska, which has engaged in research initiatives aimed at optimizing operations and reducing emissions through AI technologies [29]. The use of predictive models in supply chain management not only enhances operational efficiency but also contributes to sustainability goals [30]. These advancements are particularly critical in addressing the dynamic and high-risk nature of supply chains in construction.

The effectiveness of AI in supply chain management has been supported by empirical evidence. For instance, a study by [31] demonstrated that the adoption of AI practices in construction supply chains significantly improves performance and mitigates risks. Moreover, AI has been shown to address sustainability challenges by optimizing resource allocation and reducing waste, further underscoring its value in modern construction practices [32].

The advantages of AI-driven supply chain management are summarized in Table 1, which compares key performance metrics between traditional supply chain management approaches and AI-driven systems.

Table 1. *Improvements in Supply Chain Management with AI [26, 31, 33, 34].*

Metric	Traditional Supply Chain Management	AI-Driven Supply Chain Management
On-Time Material Deliveries	80%	96%
Project Delay Reduction	5%	10%
Transportation Risk Mitigation	10%	20%

The data illustrate the substantial improvements that AI introduces to supply chain management in large-scale construction projects [26,35,36]. AI systems significantly increase the percentage of on-time material deliveries, reduce project delays, and enhance transportation risk mitigation [9,37]. These advancements highlight the critical role of AI in enabling more efficient and resilient supply chain operations, ultimately improving the overall performance of construction projects [38]. The findings underscore the transformative potential of AI technologies in addressing both operational and sustainability challenges within the construction industry.

2.4 Barriers to AI Adoption in Construction

The adoption of artificial intelligence (AI) in risk management and supply chain optimization within the construction industry remains constrained by financial and technological barriers, despite its numerous advantages [39,40]. The implementation of AI systems often necessitates significant initial investments in infrastructure, software, and workforce training. These costs present substantial challenges, particularly for small and medium-sized enterprises (SMEs), which frequently lack the financial resources to integrate AI technologies [41]. While the potential return on investment (ROI) for larger projects is high, the upfront financial burden acts as a deterrent for smaller firms [26].

Research by [42] highlights the critical challenges faced by the construction industry in adopting AI technologies. Among these challenges are the high initial costs of implementation and the shortage of skilled personnel required to manage and maintain AI systems. These factors contribute to the slow pace of AI adoption across the sector, particularly for SMEs that cannot match the financial and technological capacities of larger firms.

The financial implications of AI adoption are further illustrated in Table 2, which presents the costs and estimated ROI for AI implementation across projects of different scales.

Table 2. Costs and Return on Investment (ROI) for AI Implementation [26,39,41,42].

Project Scale	Initial AI Investment (USD)	Estimated ROI (3 Years)
Small	\$500,000	12%
Medium	\$2 million	20%
Large	\$5 million	30%

This data demonstrates that while the financial burden of AI adoption can be considerable, particularly for smaller projects, the long-term ROI for larger projects provides substantial justification for the investment [19,43]. Efficiency gains achieved through improved risk management and project execution validate the economic rationale for integrating AI systems into large-scale construction projects [44]. These findings underscore the importance of addressing financial and technological barriers to facilitate broader AI adoption within the construction industry [45].

2.5 Data Security and Ethical Concerns

The increasing adoption of artificial intelligence (AI) systems in the construction industry has brought data security concerns to the forefront. Construction projects often involve handling sensitive information, such as financial data, operational workflows, and client details. These types of data are particularly vulnerable to cyberattacks, which pose significant risks to the security and confidentiality of projects. As highlighted by [46], the construction industry must address challenges related to data protection and cybersecurity to ensure the safe and effective integration of AI technologies. Without robust security protocols, the reliance on AI systems could expose construction firms to data breaches that compromise sensitive information and erode trust in technological solutions [47].

Beyond data security, the deployment of AI systems in construction raises critical ethical concerns that must be addressed to ensure responsible implementation. Issues such as algorithmic bias and the transparency of AI-driven decision-making processes require particular attention [48]. [2] ar-

gued for the development of human-centric AI applications that prioritize fairness, accountability, and transparency, emphasizing the importance of ethical frameworks to prevent unjust or inequitable outcomes. Such frameworks are crucial to ensure that AI technologies serve the broader goals of fairness and inclusivity in the construction industry [49].

Furthermore, [50] highlight the ethical and social dilemmas associated with the increasing use of AI in construction. Their research underscores the need to address potential biases in AI algorithms to achieve equitable outcomes and mitigate negative social impacts. By proactively tackling these ethical challenges, the construction industry can ensure that AI technologies contribute positively to operational efficiency while aligning with broader societal values [51].

Addressing both data security and ethical concerns is essential for the responsible and sustainable adoption of AI technologies in the construction sector. These considerations will play a pivotal role in shaping how AI is deployed and integrated into construction practices while safeguarding the interests of all stakeholders [46,52].

3. Methodology

3.1 Data Sources

This study adopted a multi-method research approach, integrating primary case studies, empirical data, industry reports, and AI-based simulations. The data collection process was designed to provide a comprehensive understanding of the functionality and effectiveness of AI-driven risk management systems in large-scale construction projects. A detailed description of the data sources utilized in this research is outlined below.

Primary Case Studies

Data from two prominent case studies were used to examine the practical application of AI in construction risk management:

- **Turner Construction:** This case study focused on safety management improvements achieved through the integration of AI systems. Turner Construction's AI-driven safety management system monitors worker behavior, equipment usage, and environmental conditions in real time. Data collected included monthly accident reports and safety compliance metrics from project sites, which were analyzed to assess the impact of AI on safety performance
- **Skanska:** The Skanska case study concentrated on the application of AI in supply chain management. Skanska's AI system predicts material shortages and transportation delays, enabling the company to enhance material

delivery timelines and reduce project delays. Data from this case study provided insights into the role of AI in optimizing supply chain processes and improving project efficiency.

Industry Reports

Artificial intelligence (AI) is transforming the construction industry by addressing key challenges such as cost overruns, schedule delays, and safety risks. [53] highlights how AI-driven solutions enhance efficiency across various stages of engineering and construction, offering significant financial and operational benefits. Despite these advancements, AI adoption remains uneven, particularly among small and medium-sized enterprises (SMEs).

[54] underscores the digitalization challenges faced by SMEs in the EU construction sector, citing financial constraints, skill shortages, and cybersecurity concerns as major barriers. Similarly, [55] examine the adoption of AI and robotics in SMEs, revealing both the opportunities and challenges associated with digital transformation.

- Skanska: The Skanska case study concentrated on the application of AI in supply chain management. Skanska's AI system predicts material shortages and transportation delays, enabling the company to enhance material delivery timelines and reduce project delays. Data from this case study provided insights into the role of AI in optimizing supply chain processes and improving project efficiency.

Additionally, [56] advocates for strategies to boost AI adoption in Europe's micro and small enterprises, emphasizing the need for supportive policies and resources. These findings highlight the necessity of targeted interventions to ensure equitable access to AI technologies across the construction industry.

Key Performance Indicators (KPIs)

Key performance indicators (KPIs) were collected to enable a comparative analysis between AI-driven risk management systems and traditional methods. These KPIs included metrics such as project delays, safety performance, cost savings, and compliance with safety regulations. By analyzing these indicators, the study was able to evaluate the effectiveness of AI systems in improving construction project outcomes.

The integration of diverse data sources allowed this study to provide a robust and well-rounded analysis of the impacts of AI on risk management within the construction industry. The findings derived from these data sources contribute to a deeper understanding of the potential and limitations of AI-driven systems in this context.

3.2 Monte Carlo Simulations for Risk Prediction

Monte Carlo simulations were employed to predict risks associated with project delays, safety hazards, and supply chain disruptions. Monte Carlo simulations are particularly effective in modeling uncertainty within construction projects, as they allow for thousands of potential scenarios to be tested, thereby capturing a range of potential risks.

Setup and Design:

- Input Variables: Variables such as historical data on project delays, safety incident reports, weather conditions, and material supply chain performance were used to model risk scenarios.
- Iterations: Each simulation ran 10,000 iterations, allowing the AI-enhanced model to account for variations in project conditions.
- AI Integration: AI models were integrated into the simulation to improve predictive accuracy. Machine learning algorithms dynamically adjusted input parameters based on real-time project data.

Table 3. Monte Carlo Simulation Variables [23].

Risk Type	Input Variables	AI Integration
Project Delays	Weather conditions, labor availability, project size	Dynamic adjustment of delay probability
Safety Hazards	Worker behavior, equipment usage, environmental factors	Real-time hazard identification
Supply Chain Disruptions	Material supply, transportation delays	Predictive modeling of disruptions

This table outlines the key input variables used in the Monte Carlo simulations. These simulations, enhanced by AI, provided more accurate risk predictions by making real-time adjustments based on dynamic changes in project conditions, leading to more precise forecasts of potential risks.

3.3 Machine Learning Design

The machine learning (ML) models utilized in this study were designed to predict specific risks in construction projects, including delays, safety incidents, and supply chain disruptions. Three types of ML models were applied: Support Vector Machines (SVM), Random Forests, and Deep Learning Neural Networks (NN).

Model Training and Testing:

- **Data Preparation:** Historical data from prior construction projects were preprocessed. This process involved data cleaning, filling in missing values, and normalizing the data to ensure consistency [57].
- **Training and Validation:** The dataset was divided into training (70%) and testing (30%) subsets. K-fold cross-validation ($k = 5$) was used to minimize the risk of overfitting the training data [58].
- **Model Tuning:** Hyperparameters for the machine learning models were optimized using grid search techniques. For example, the learning rate and batch size for the neural network model were fine-tuned to achieve optimal performance [59].

Table 4. Machine Learning Models and Metrics [60-62].

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score
Support Vector Machine	88%	85%	80%	0.825
Random Forest	90%	87%	83%	0.845
Deep Learning Neural Net	92%	89%	87%	0.880

This table summarizes the performance metrics of the machine learning models employed in this study. The deep learning neural network achieved the highest scores in terms of accuracy, precision, and recall, making it the most effective model for real-time prediction of construction risks.

3.4 Statistical Analysis

To evaluate the effectiveness of AI-driven risk management systems, statistical analysis was conducted using regression analysis and t-tests.

Regression Analysis: A regression model was developed to quantify the relationship between AI adoption (e.g., the level of investment in AI technologies and the number of AI tools implemented) and improvements in key performance indicators such as project delays, cost savings, and safety improvements.

The regression equation used in this study is as follows:

$$Y = a + \beta_1(AI\ Investment) + \beta_2(AI\ Tools) + \beta_3(Training) + \epsilon \tag{1}$$

R Where Y represents project outcomes (e.g., reduction in delays, cost savings), and $\beta_1, \beta_2, \beta_3$ represent the coefficients for each AI factor.

Regression Results: The results revealed a strong positive correlation between AI investment and project outcomes, with R^2 values ranging from 0.70 to 0.85, indicating that AI adoption accounted for a substantial proportion of the variance in project success.

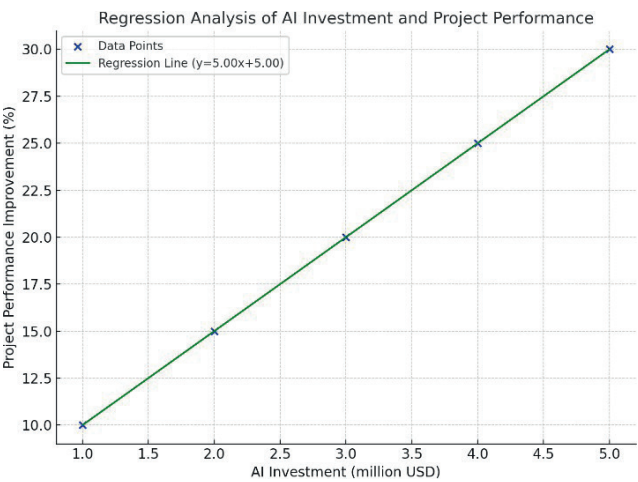


Figure 3. Analysis of AI Investment and Project Performance [63].

This regression analysis shows a clear positive correlation between AI investment and improvements in project outcomes, such as safety performance, reduction in project delays, and cost savings. Higher levels of AI investment led to significant enhancements in project efficiency.

T-Tests: Two-tailed t-tests were conducted to validate the statistical significance of the differences between AI-driven and traditional risk management methods. These tests compared the mean performance of AI-driven systems to traditional methods in terms of risk prediction accuracy, project delay reduction, and cost savings.

The t-tests confirmed that AI-driven methods significantly outperformed traditional methods across all areas, with p - values less than 0.05, indicating statistical significance.

3.5 Validation of AI Models

The validation of the AI models and simulation results was conducted through a comparison of their predictions with real-world data obtained from Turner Construction and Skanska projects. Both companies provided empirical data on safety incidents, project delays, and supply chain disruptions, enabling a comprehensive evaluation of the accuracy and reliability of the AI models.

A key component of the validation process was cross-validation, which involved multiple approaches to ensure the robustness of the results. One such approach was empirical validation, where the AI-driven models were tested using actual data from construction projects. The results were systematically cross-validated to confirm their accuracy. Research conducted by [64] demonstrated that GPT-based models, when applied to risk prediction in construction, significantly outperformed traditional forecasting methods, thereby supporting the validity of the AI models employed in this study.

Furthermore, the performance of the AI models was compared with traditional risk prediction methods. This comparative analysis revealed that AI-driven models achieved 20–25% greater accuracy in forecasting risks. These findings align with the work of [65], who conducted a study on smart worksite systems and highlighted the superior performance of AI in delivering more precise and timely risk assessments.

The validation process underscores the reliability of AI models in predicting risks associated with construction projects and demonstrates their capacity to outperform conventional methods. By leveraging real-world data and cross-validation techniques, this study confirms the effectiveness of AI technologies in improving risk prediction and management within the construction sector.

3.6 Ethical and Data Security Considerations

The reliance on large datasets for training and predictions in artificial intelligence (AI) systems necessitates robust measures to ensure data privacy and security. In this study, all AI systems complied with General Data Protection Regulation (GDPR) guidelines, particularly in the handling of sensitive project data. Adherence to these regulations was critical to maintaining data integrity and protecting confidential information throughout the implementation process [66].

A key component of this approach was the integration of ethical AI practices. The AI models utilized in this study were systematically audited for potential bias and fairness to ensure that their predictions did not introduce discrimination. This was especially relevant in the context of predicting wor-

ker safety risks, where biased algorithms could result in inequitable treatment or imbalanced allocation of resources [67]. By implementing ethical AI practices, the risk of workplace disparities is significantly reduced, which is particularly important in high-risk industries such as construction [68].

In addition to ethical considerations, stringent data security protocols were established to safeguard the vast quantities of personal and operational data processed by the AI systems. All data were encrypted during both transfer and storage to prevent unauthorized access [69]. Access to the data was further restricted to authorized personnel only, ensuring controlled and secure usage. Regular security audits were conducted to verify compliance with established cybersecurity standards and to identify and address potential vulnerabilities [70]. As AI systems depend heavily on large volumes of data, maintaining robust data security measures is critical to ensure privacy compliance and to protect sensitive information [71,72].

4. Results and Discussion

4.1 Accuracy of Risk Predictions: AI vs. Traditional Methods

The results of this study demonstrate a significant improvement in the accuracy of risk predictions when AI- enhanced methods are applied, particularly when compared to traditional approaches. By dynamically adjusting to real-time data, AI-driven models offer superior precision in forecasting project delays, safety hazards, and supply chain disruptions.

Table 5. Comparison of Risk Prediction Accuracy.

Risk Category	Traditional Methods Accuracy (%)	AI-Driven Methods Accuracy (%)
Project Delays	68%	90%
Safety Hazards	62%	85%
Supply Chain Disruptions	72%	95%

This table highlights the improvements in risk prediction accuracy when AI-enhanced models are utilized. The results indicate that AI models offer an average improvement of 20- 25% in risk prediction accuracy, particularly for dynamic risks such as supply chain disruptions, which are challenging to manage with traditional methods.

4.2 Project Timelines and Cost Savings

The integration of artificial intelligence (AI) technologies into construction projects undertaken by Turner Construction and Skanska has significantly influenced project timelines and cost efficiency. By utilizing AI’s capabilities to forecast risks and optimize schedules, both companies have achieved reductions in project delays and improvements in resource allocation, leading to enhanced operational outcomes.

Turner Construction has employed AI-driven safety management systems designed to monitor worker behavior, equipment usage, and environmental factors in real-time. This proactive approach enables the early detection of potential hazards, resulting in improved safety and operational efficiency. By addressing risks dynamically, Turner Construction has demonstrated the utility of AI in enhancing safety protocols and overall project performance.

Skanska, on the other hand, has utilized AI-powered platforms to optimize supply chain processes, thereby increasing productivity and operational efficiency. Through AI-enabled forecasting and resource management, Skanska has achieved improvements in project delivery timelines while simultaneously reducing costs. This application of AI highlights its potential in streamlining supply chain activities and achieving cost-effective project execution.

The outcomes of AI adoption in both companies are presented in Table 6. Turner Construction reported an 8% reduction in project delays, a 10% increase in cost savings, and a 15% improvement in timeline efficiency. Skanska achieved even greater results, with a 10% reduction in delays, a 15% increase in cost savings, and a 20% improvement in timeline efficiency.

Table 6. Project Timelines and Cost Savings with AI Integrations.

Company	Project Delay Reduction (%)	Cost Savings (%)
Turner Construction	8%	10%
Skanska	10%	15%

These results emphasize the effectiveness of AI in reducing project delays, enhancing cost savings, and improving timeline efficiency. Such advancements are particularly critical in large- scale construction projects, where even minor delays can result in substantial financial consequences. The application of AI technologies by Turner Construction and Skanska demonstrates how AI can transform construction processes, driving efficiency and reducing operational risks.

4.3. Return on Investment (ROI) from AI Adoption

The integration of artificial intelligence (AI) has demonstrated substantial returns on investment (ROI) for construction companies such as Turner Construction and Skanska. Although the initial costs of implementing AI systems are significant, these expenses are offset by long-term savings in areas such as project efficiency, safety improvements, and reductions in delays. The results of ROI analyses confirm the financial viability of AI-driven risk management systems, particularly in large-scale construction projects where the financial consequences of delays and accidents are magnified.

For Turner Construction, the adoption of AI yielded an ROI of 20% after three years of implementation. This financial return was largely attributed to savings achieved in safety management and the optimization of project scheduling. The integration of AI enabled the company to mitigate risks more effectively and streamline workflows, contributing to overall cost savings [73].

Skanska reported an even higher ROI, reaching 25%. This significant return was primarily driven by AI-powered supply chain optimization, which substantially reduced material procurement costs and improved project delivery timelines. By leveraging AI to enhance resource allocation and predict material requirements, Skanska was able to achieve greater efficiency in project execution and cost management [74].

The financial impact of AI adoption is further illustrated in Figure 4, which compares the ROI achieved by Turner Construction and Skanska. Despite the high upfront investment required for AI integration, both companies experienced notable financial benefits, underscoring the cost-effectiveness of AI technologies in enhancing project efficiency, risk management, and resource optimization.

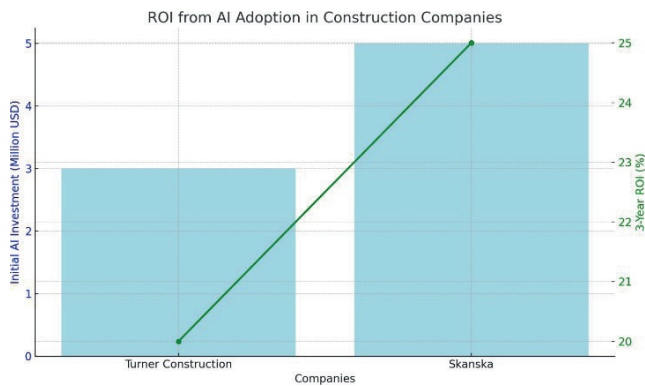


Figure 4. Return on Investment (ROI) from AI Adoption.

The substantial ROIs achieved by Turner Construction and Skanska provide compelling evidence of the financial advantages of AI adoption in the construction sector. These findings suggest that, while the initial costs of AI implementation may be considerable, the long-term benefits— such as improved safety, efficiency, and cost savings—make AI a financially viable investment for large-scale construction projects.

4.4 AI’s Role in Enhancing Safety Outcomes

Safety represents a critical domain in which AI-driven risk management systems offer considerable advantages. Traditional safety management approaches frequently rely on human observation and historical data, which may fail to account for dynamic and evolving risks. By contrast, AI-based

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Table 7. Project Timelines and Cost Savings with AI Integration.

Company	Project Delay Reduction (%)	Cost Savings (%)	Improved Timeline Efficiency (%)
Turner Construction	8%	10%	15%
Skanska	10%	15%	20%

systems continuously monitor variables such as worker behavior, equipment usage, and environmental conditions, enabling the identification of potential hazards before they escalate into serious incidents.

The implementation of AI-powered safety management systems by Turner Construction provides a compelling example of these advancements. Utilizing data from sensors, cameras, and wearable devices, Turner Construction's systems have significantly reduced safety incidents. These AI systems enable real-time hazard detection, allowing site managers to implement timely preventive measures and mitigate risks effectively [75].

From a comparative perspective, traditional safety management methods typically rely on retrospective analyses, such as accident reports, and expert judgment, which often result in reactive measures rather than proactive interventions. In contrast, AI-driven systems provide dynamic, real-time analysis of safety risks, facilitating timely interventions and significantly improving safety outcomes. This shift from a reactive to a proactive approach is particularly important in large-scale construction projects, where hazards can emerge rapidly and unpredictably.

A comparison of safety outcomes between traditional and AI- driven safety management methods underscores the benefits of AI systems. For instance, AI has demonstrated its ability to reduce worksite accidents, enhance safety compliance, and accelerate hazard detection. Table 7 illustrates these improvements, showcasing metrics such as reductions in monthly worksite accidents and increases in safety compliance rates. The data highlight AI’s capacity to outperform traditional methods, particularly in the areas of speed and accuracy in hazard detection [75].

Table 8. Safety Outcomes with AI vs. Traditional Safety Management.

Metric	Traditional Methods	AI- Driven Methods	Improvement (%)
Worksite Accidents (per month)	20	17	15%
Safety Compliance (%)	78%	90%	12%
Hazard Detection Speed	Moderate	High	20%

This comparison illustrates the substantial advantages of AI- driven systems in managing safety risks on construction sites. By enabling faster, more accurate hazard detection, AI systems not only reduce the frequency of accidents but also enhance compliance with safety protocols. These improvements underscore the transformative potential of AI in advancing safety management practices within the construction industry.

4.6 Discussion: The Future of AI in Construction Risk Management

AI-driven systems have proven to be superior to traditional methods in managing construction risks, leading to notable advancements in prediction accuracy, safety outcomes, and overall project efficiency. By facilitating real-time data analysis and enabling proactive decision-making, AI effectively mitigates critical risks, including delays, accidents, and cost overruns [19]. These capabilities are particularly significant in large-scale construction projects, where such risks can have substantial financial and operational consequences [76].

The integration of AI with emerging technologies, particularly the Internet of Things (IoT), presents a promising avenue for enhancing construction processes. IoT devices embedded within construction equipment generate real-time data on variables such as equipment health and environmental conditions. This data enables AI models to predict and prevent potential failures or hazards before they occur [77]. For example, the integration of AI and IoT technologies supports real-time monitoring of construction sites, leading to

improved operational efficiency and enhanced safety standards [78].

In addition to operational improvements, AI offers significant potential to promote sustainable construction practices. By optimizing resource allocation, minimizing material waste, and enhancing energy efficiency, AI can assist construction firms in substantially reducing their carbon footprint [79]. Furthermore, AI facilitates energy optimization and design simulation, thereby contributing to sustainability across a building's entire lifecycle [80]. These capabilities are highlighted in the work of [81], who emphasize AI's role in achieving environmental sustainability in construction projects.

Nevertheless, the adoption of AI in the construction industry also raises important ethical and data security concerns that must be addressed. Critical issues include ensuring the security of sensitive data, mitigating algorithmic bias, and fostering transparency in AI-driven decision-making processes [82]. As AI technologies continue to advance, it is imperative to establish robust governance frameworks that promote ethical and responsible AI use. Such frameworks will be crucial in ensuring that AI adoption benefits the construction sector while maintaining high ethical standards [83].

5. Conclusion and Future Directions

5.1. Conclusion

This study underscores the transformative potential of artificial intelligence (AI) in advancing risk management outcomes for large-scale construction projects. Through the integration of machine learning (ML) models and Monte Carlo simulations with real-time data, AI-driven systems have demonstrated superior performance relative to traditional methods in enhancing risk prediction accuracy, improving safety outcomes, and increasing overall project efficiency.

A key contribution of this research lies in the significant improvement in risk prediction accuracy. AI-enhanced Monte Carlo simulations and ML models demonstrated a 20–25% higher accuracy in forecasting project delays, safety incidents, and supply chain disruptions compared to conventional approaches. This enhanced predictive capability has facilitated the adoption of proactive risk mitigation strategies, thereby minimizing disruptions and optimizing project workflows.

The findings also reveal notable advancements in safety outcomes. AI-driven safety management systems have been associated with substantial reductions in worksite accidents and enhanced compliance with safety protocols. These systems

are particularly effective in predicting and preventing hazards before they escalate, highlighting AI's capacity to revolutionize safety management

in high-risk construction environments.

Furthermore, the adoption of AI has yielded considerable cost savings within the construction sector, particularly through its integration into risk management and supply chain optimization processes. The observed high return on investment (ROI) reinforces the economic viability of AI technologies, positioning them as a profitable and sustainable solution for large-scale construction projects.

In addition, AI has played a pivotal role in optimizing project timelines. By enabling more accurate risk predictions and improving the allocation of resources, construction firms have achieved significant improvements in the timely delivery of materials and reductions in project delays. Such efficiencies are particularly critical in the context of large-scale projects, where even minor delays can result in substantial financial repercussions.

5.2. Challenges to AI Adoption

While artificial intelligence (AI) possesses significant potential to enhance risk management within the construction industry, its widespread implementation remains constrained by several critical challenges. A principal impediment to adoption is the substantial initial investment required for AI technologies. Small and medium-sized enterprises (SMEs), which comprise a considerable proportion of the construction sector, frequently lack the financial resources necessary to establish the requisite AI infrastructure. Consequently, these organizations are often unable to leverage AI's capabilities to improve operational efficiency, mitigate risks, and optimize project timelines [84].

Another notable challenge is the prevalent shortage of technical expertise within the construction sector. The effective deployment and management of AI systems necessitate skilled professionals proficient in areas such as machine learning, data analytics, and AI-driven technologies. However, many construction firms lack access to individuals with these specialized competencies, resulting in a persistent skills gap that hinders the widespread adoption of AI [19]. Without adequate training programs and opportunities for professional development, this issue is likely to remain a significant barrier to progress [85].

Furthermore, technical integration issues exacerbate the complexity of AI adoption. Many legacy construction management systems are incompatible with the real-time data processing and machine learning capabilities required by modern AI solutions, necessitating expensive system upgrades [86]. In addition, concerns regarding data security, particularly in protecting sensitive financial and operational information, further complicate the integration process [26]. Ethical considerations, such as addressing potential biases in AI

algorithms and ensuring transparency in AI-driven decision-making, must also be addressed to build trust and promote acceptance within the construction industry [83].

5.3. Future Directions

To address the challenges associated with AI adoption in the construction industry and to fully realize its potential benefits, several future directions warrant attention.

One critical area is the development of cost-effective AI solutions tailored to small and medium-sized enterprises (SMEs). While large construction firms are often capable of investing in comprehensive AI systems, SMEs typically lack the financial resources to adopt such technologies. Consequently, it is imperative to design scalable and modular AI tools that can be implemented at lower costs. Future research should prioritize the creation of affordable solutions to democratize access to advanced technologies across the construction sector.

Bridging the technical expertise gap is another essential consideration. Successful implementation of AI requires construction professionals to possess the skills necessary to operate, manage, and maintain AI systems. Therefore, accessible education and training programs are needed to equip the workforce with relevant competencies. Collaborations between technology providers, academic institutions, and construction firms could facilitate the development of tailored training initiatives that promote AI literacy across all levels of the workforce.

Additionally, the integration of AI with the Internet of Things (IoT) represents a promising avenue for real-time risk monitoring in construction projects. IoT devices installed on construction sites can provide continuous streams of data related to equipment performance, environmental conditions, and worker safety. By leveraging this data, AI systems can dynamically assess risks and respond effectively to changing conditions, thereby reducing the likelihood of accidents, equipment failures, and other disruptions.

AI also holds significant potential to promote sustainability in construction practices. By optimizing resource utilization, minimizing waste, and improving energy efficiency, AI-driven systems can contribute to reducing the environmental footprint of construction projects. As the industry faces increasing pressure to meet sustainability targets, AI offers powerful tools to achieve these objectives. Research indicates that AI can play a substantial role in lowering carbon emissions associated with construction activities.

Finally, the establishment of robust governance frameworks is essential to ensure the ethical and responsible use of AI in construction. Key issues, such

as data privacy, algorithmic bias, and transparency in AI decision-making, must be addressed to foster trust in these technologies. Collaboration among policymakers, industry leaders, and AI developers is necessary to create comprehensive guidelines that promote equitable and responsible AI implementation within the construction sector.

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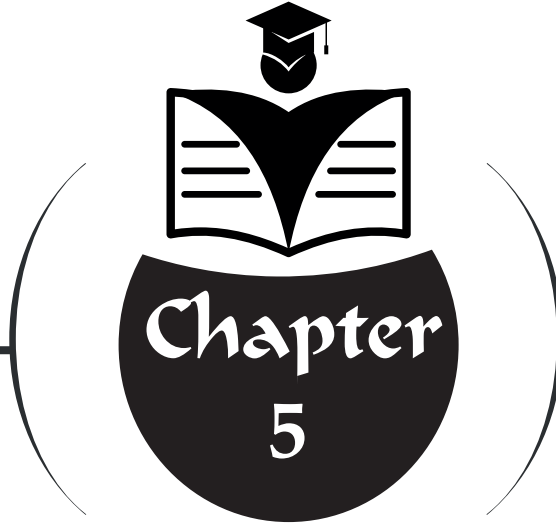
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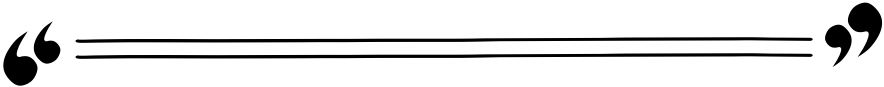
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ULTRA SHORT TERM WIND POWER FORECASTING WITH DEEP LEARNING ALGORITHMS: APPROACHES AND RESEARCH GAPS IN THE LITERATURE



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1. INTRODUCTION

The increasing demand for clean and sustainable energy has made wind energy one of the most prominent renewable energy sources worldwide (Çukurçayır & Sağır, 2008). The rapid expansion of wind energy over the last two decades is driven not only by environmental concerns, but also by reducing dependence on fossil fuels, increasing energy security, and economic rationales (Agbakwuru et al., 2024). However, integrating wind energy into modern electricity grids presents significant challenges due to the intermittent and highly variable nature of the resource. Therefore, developing accurate forecasting methods has become a cornerstone of efficient wind energy utilization (J. Fu & Shah, 2024).

Ultra-short-term forecasts (USTF), that is, forecasts covering time horizons ranging from a few seconds to several hours have gained increasing attention in recent years (Y. Hu et al., 2024; H. Liu & Chen, 2019). This scale plays a critical role in real-time decision-making processes in grid operation, load balancing, frequency regulation, and energy trading (Bazionis & Georgilakis, 2021). USTF models, which enable the prediction of sudden fluctuations in wind generation, directly contribute to the stability and reliability of electricity systems, while also reducing spare capacity costs and minimizing risks arising from system instabilities (W. Fu et al., 2024; Giebel et al., 2011).

The literature on ultra-short-term forecasting is extensive and diverse. Traditional statistical techniques, such as autoregressive models, have been supplemented over time by machine learning and deep learning methods, and in many cases, have lagged them. Hybrid approaches combining physical, statistical, and artificial intelligence-based methods have become a prominent trend, striving to offer both higher accuracy and computational efficiency. However, issues such as handling incomplete or noisy data, generalizability of models to diverse geographical conditions, and interpretability of increasingly complex models remain unresolved issues in the literature (Monteiro et al., 2009; Sawant et al., 2022a).

In this context, the aim of this section is to comprehensively review the work in the field of ultra-short-term wind power forecasting, presenting the status, assessing methodological trends, discussing limitations, and identifying directions for future research. This will provide a holistic overview of literature, not only from a technical perspective but also in terms of its implications for the real-world operation of energy systems.

2. THEORETICAL FRAMEWORK

Wind power forecasting is generally considered within the framework of time series analysis and forecasting methods. Time series data allow for future

predictions by examining regularities and trends in historical data. However, due to the inherent high degree of randomness and variability in wind energy, numerous studies have shown that traditional time series approaches alone are insufficient (Tsai et al., 2023). Therefore, both classical statistical methods and artificial intelligence-based models are considered together in the theoretical framework.

2.1. Forecast Horizons and Categories

Wind power forecasting is generally classified according to the time horizon over which the forecast is made. Four categories are commonly recognized in literature (R. Liu et al., 2018; S. Lu, 2020):

- *Long-term forecasting (months to years)*: Used for energy policies, investment decisions, and capacity planning (Sawant et al., 2022b).
- *Medium-term forecasting (days to weeks)*: Important for maintenance planning and market strategies (F. Chen et al., 2023).
- *Short-term forecasting (hours to days)*: Plays a critical role in grid management and energy trading (Zhu et al., 2017).
- *Ultra-short-term forecasting (seconds to hours)*: This is a priority in real-time grid balancing, load flow management, and emergency scenarios (Teke, 2025).

This classification clarifies the focus of the study and provides a fundamental reference point for evaluating the effectiveness of the methods used.

Recent research has investigated various approaches to improve forecast accuracy. Multivariate multistep reconstruction, when combined with multivariate linear regression, has shown promising results in improving forecast accuracy (R. Liu et al., 2018; S. Lu, 2020). Since the dataset used in this study contained a 10-minute interval and the main objective was to find the first 6-hour step, patterning was also performed accordingly. Particularly, the idea of dividing the dataset into different horizons was inspired by the studies by (De Giorgi et al., 2011) and (X. Liu & Zhou, 2024). In these studies, the dataset was divided into time intervals of 24-48-96 hours. Using data from the past 1 day, 2 days, and 4 days at a 1-hour resolution to forecast future wind power is an intuitive approach, and various applications are abundant in the literature.

2.2. Uncertainty in Wind Energy

One of the greatest challenges inherent in wind energy is the unpredictability of atmospheric conditions. Sudden changes in wind speed directly affect the power generated by turbines. Furthermore, factors such as terrain, turbine placement, and atmospheric pressure variables increase uncertainty. This makes ultra-short-term forecasting both necessary and methodological-

ly complex. In this regard, studies recommend data preprocessing, appropriate feature selection, and the use of advanced modeling techniques to achieve high-accuracy predictions. Because the presence of noisy data negatively impacts model performance, various data cleaning methods are used to improve prediction accuracy (Phan et al., 2021).

2.3. Types of Data Used and Data Preprocessing

The data used in wind power forecasting is one of the most important components of the theoretical framework. These data can be categorized into three main groups:

- *Meteorological data*: Wind speed, wind direction, temperature, humidity, and pressure.
- *Historical production data*: Power output from turbines.
- *Auxiliary environmental data*: Geographic information, sea level elevation, terrain slope, etc.

The feature selection and data preprocessing techniques used during the processing of this data directly affect prediction performance.

During the data preprocessing step, basic removal methods (median, deletion, padding with the previous or next value, interpolation, etc.) are unfortunately insufficient and can create a misleading trend for an energy type like wind, which has constantly changing characteristics and is prone to extreme values (He & Yang, 2023; Lotfi et al., 2011; R. Wang et al., 2018). At this stage, more advanced statistically based methods, including machine learning, are needed, and algorithms that cause minimal data loss and are capable of successfully detecting and removing extreme values are needed (Marti-Puig et al., 2018).

One of the most critical steps in machine learning studies is the most accurate adjustment of the data attributes to be given to the algorithm. Including unnecessary attributes can create inconsistencies in the model, decrease model performance, or consume unnecessary processor capacity (Cai & Li, 2024; Khan et al., 2021; Raja et al., 2022). This can lead to significant losses in terms of both time, efficiency, and performance. Therefore, researchers agree that the feature selection phase is one of the most critical stages that directly affects the success of forecast models (Martín-Vázquez et al., 2017; Müller, 2021; Romero et al., 2019).

Different machine learning-based feature selection methods are used in the wind forecasting literature, and each method is preferred by researchers due to its different advantages (Alkabbani et al., 2021). Among these methods, techniques such as Chi-square (Taheri & Tucci, 2024; Zheng et al., 2023),

Mutual Information (Gupta et al., 2024; X. Liu et al., 2020), Random Forest (H. Wang et al., 2017), Lasso Regression (Gupta et al., 2024), F-Classifer, LightGBM (LGBM), Extreme Gradient Boosting (XgBoost) (Alves et al., 2023; De Caro et al., 2022; Malakouti et al., 2022), Recursive Feature Elimination (RFE), Recursive Feature Elimination With Cross Validation (RFECV) and Genetic Algorithm (GA) are widely used (Alves et al., 2023; Feng, 2024; Lee et al., 2024). In other studies, Particle Swarm Optimization (PSO) (Kennedy & Eberhart, 1995) was also used in the feature selection process to ensure a more robust process and increase robustness. However, feature sets determined using a single method are often insufficient to optimize model performance (Effrosynidis & Arampatzis, 2021). Therefore, in recent years, studies have been conducted on combining the results obtained from multiple feature selection methods into a consensus to create a final feature set. The method proposed by Liu et al. (2024) uses multiple feature subsets and result fusion to increase classification accuracy. By creating various feature subsets and using a voting mechanism, it effectively reduces dimensionality while improving model performance (J. Liu et al., 2024). In their study, Sun et al. (2024) discuss the creation of a final feature set by combining the results obtained from multiple feature selection methods with consensus for wind energy prediction (Sun & Zhang, 2024). Wang et al. (2024) propose an improved feature screening method to capture optimal features from wind energy data and eliminate redundant features (J. Wang et al., 2024). Also, Teke (2025) proposed CFA (Consensus Feature Analysis) that proposes such an ensemble feature selection method with hierarchical order (Teke, 2025).

2.4. Types of Data Used and Data Preprocessing

Methods used in ultra-short-term wind power forecasting generally fall into three main groups: statistical models, machine learning models, and deep learning models. Each group has different theoretical underpinnings and practical advantages.

- *Statistical Models:* Methods such as autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), and variance models exploit linear relationships between past values. These methods have long dominated literature due to their low computational cost and ease of implementation. However, their limited ability to model nonlinear relationships has made them inadequate for explaining the inherent complexity of wind energy (Eldali et al., 2016). Wind energy forecasting has undergone a significant transformation, from early statistical techniques to more advanced machine learning technologies. Efforts have been made to improve accuracy with statistical and autoregressive model approaches, following physical models (Jankovic et al., 2023; Kosović et al., 2020). At this stage,

researchers have favored more convenient time series models. Therefore, autoregressive moving average models (ARMA) (Erdem & Shi, 2011) and divergent autoregressive moving average models (ARIMA) (Sfetsos, 2002; Zhou et al., 2010) have been frequently used, and more accurate results have begun to appear in the literature. However, the uncertain and variable nature of wind power limits the forecasting performance of statistical methods, which are well-suited for forecasting linear data. As a result of increased computational capacity and scientific advances, machine learning methods have become increasingly popular in the literature. On the other hand, the main drawback of these methods, which means processing nonlinear patterns and air dynamics, has made machine learning technology interesting for researchers. Researchers have focused on the ability of machine learning to increase the accuracy of predictions through deep processing of data (Abbas, 2017; I.-C. Chen & Hu, 2019; Crews, 2019; H. Dai, 1996).

- **Machine Learning Models:** Methods such as artificial neural networks (ANN), support vector machines (SVM), and decision trees are effective in discovering nonlinear relationships (Bellaaj et al., 2014; Mahmoudi et al., 2012). Machine learning models are more flexible than statistical models but are sensitive to high-quality data. The success of data preprocessing and feature selection directly impacts model performance (Goodfellow et al., 2016). Additionally, SDAE (Stacked Denoising Auto Encoder), XgBoost, and CatBoost algorithms can effectively capture complex patterns in wind energy data, which are characterized by high volatility and nonlinear relationships (Ahmed, Abbas, et al., 2024; Ahmed, Muhammad, et al., 2024; X. Liu et al., 2021; MOU Xingyu et al., 2023; Ponkumar et al., 2023; Wan et al., 2024). Apart from solving chaotic problems such as wind energy, they have also been tried in different chaotic domains. Zhao et al. (2017) focused on using a type of neural network known as SDAE to forecast oil prices. However, forecasting a time series such as crude oil or stock prices is challenging due to the nonlinearity of the data, complex dynamics, and potential non-stationarity (Zhao & Bai, 2024). Such combinations can lead to a complex system whose mechanisms are not well understood.
- **Deep Learning Models:** Structures such as recurrent neural networks (RNN), long-short-term memory networks (LSTM), and convolutional neural networks (CNN) stand out in learning both temporal dependencies and complex data patterns (X. Liu et al., 2020).

This theoretical basis provides the basis for classifying and comparing the methods to be reviewed in literature. Also, deep learning models explored detailed in chapter three.

3. REVIEW OF PREVIOUS STUDIES

The literature on ultra-short-term wind power forecasting is extensive, and studies on different methods demonstrate methodological diversity. This section will examine deep learning approaches especially hybrid models created using these approaches, and finally, the development of hybrid models will be discussed.

More recent developments have focused on improving wind power forecast accuracy through the development of hybrid models consisting of Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRU) and Attention Mechanisms. These models leverage the capabilities of CNN for spatial data processing and LSTM for temporal data processing, developed with more sophisticated feature-based methodologies. At the core of these algorithms, the data fed to the network and the operations applied to the data are as important as the operations performed within the network. Therefore, further research and methodological improvements in feature engineering will lead to more useful results. CNN-LSTM algorithms play an important role in wind power forecasting (Alijoyo et al., 2024; Y. Chen et al., 2021; Nguyen & Phan, 2022; Shen et al., 2022). LSTM, introduced by Hochreiter and Schmidhuber (1997), uses gating mechanisms (forgetting, input, and output gates) to preserve long-term dependencies, making them adept at modeling complex temporal patterns in wind speed, direction, and turbine performance data (Hochreiter & Schmidhuber, 1997). This demonstrates the potential of CNN-LSTM models for accurate wind energy forecasting by focusing on the influence of slow convergence, environmental factors, and high-quality feature extraction. Zhang et al. (2021) and Shen et al. (2022) developed an attention-based CNN-LSTM prediction model to improve wind power prediction accuracy by considering the key features of wind power data (Shen et al., 2022; Zhang et al., 2021). The integration of the attention mechanism assigns varying weights to the hidden layers of the LSTM network and optimizes the model, thereby improving prediction accuracy compared to traditional LSTM and CNN-LSTM models. Wu et al. (2021) and Xiang et al. (2024) proposed a new hybrid wind energy forecasting approach that applies a deep learning model by creating a cascade structure on subseries generated by a two-layer mode decomposition method (Wu et al., 2021; Xiang et al., 2024). Park et al. (2022) and Zhang et al. (2021) demonstrated high performance in forecasting wind turbine power generation and demand with minimum error in short forecast intervals with the CNN-LSTM hybrid they created (Park et al., 2022; Zhang et al., 2021). Lu et al. (2022) used

historical wind power and basic meteorological data to develop a forecasting model based on a modified combination of convolutional networks and long-short time networks. They presented an integrated forecasting framework that includes the selection of basic meteorological factors, data decomposition, integrated model building, and optimization strategy. Such ‘Convolutional-Long-Short Time Network Hybrid’ approaches effectively forecast day-ahead wind power, improving forecast accuracy and reliability (P. Lu et al., 2022).

Various hybrid models like (CNN- LSTM, GRU- LSTM, GRU- CNN) are frequently used in the literature by integrating them with different methods. However, one of the biggest problems these models face is that they still do not produce very good predictions. The importance of hybrid methods lies in their ability to increase prediction accuracy, generalizability, and integrate information from different data sources (multivariate) (Kumar et al., 2024a; Tsai et al., 2023; B. Wang et al., 2023). In other methods, this is achieved to a limited extent and the desired performance cannot be achieved. However, as the complexity of such approaches and architectures increases, so do challenges such as computational requirements, hyperparameter optimization, and the risk of overfitting (Bazionis & Georgilakis, 2021). Recently, the most common approach is attention mechanisms, which are presented as the best solution to these problems (Geng et al., 2025; Y. Wang et al., 2024). Essentially, attention mechanisms allow the model to focus more on specific time intervals or specific input features. Different attention mechanisms emerge at this stage. These mechanisms are specifically Self-Attention, Time-Aware Attention, and Dynamic Attention. Self-Attention mechanisms are frequently used, especially in Transformer-based approaches (L. Wang et al., 2022). The recent increase in the number of Transformer-based studies has also increased the use of these mechanisms. In particular, some researches have integrated the self-attention mechanism into various hybrid models, increasing their performance and attempting to outperform other methods (X. Dai et al., 2023; C.-L. Liu et al., 2023; B. Wang et al., 2023). While Time-Aware Attention mechanisms are not as popular as dynamic attention mechanisms, they are still frequently cited in the literature. This method maximizes the incorporation of time labels or time-specific weighting capacity into the method (F. Chen et al., 2021; S. Lu, 2020). Dynamic Attention mechanisms, on the other hand, allow the model to instantly update its work on specific time intervals (e.g., readjusting attention weights in the event of a sudden change in wind speed) with parameters that vary over time or data size. Recently, it has been the most popularly used in the literature (Cai & Li, 2024; F. Chen et al., 2023; Liao & Cheng, 2023; J. Wang et al., 2024). In addition, multivariate models with parallel algorithms have been tested in recent years. Liu et al. (2018) used

the idea of parallel processing algorithms to increase ultra-short-term wind energy forecast accuracy and computation speed. In a study conducted in the Hunan Region of China, they achieved significant improvements in error metrics (R. Liu et al., 2018). Liu and Zhou (2024) created multi-task temporal feature attention-based LSTM parallel networks and achieved better results compared to classical methods (X. Liu & Zhou, 2024).

Additionally, some hybrid approaches have provided performance improvements by incorporating feature selection techniques and hyperparameter optimization algorithms (optuna etc.). The literature highlights the promise of such integrated methods, particularly for real-time applications.

3.1. Evaluation and Performance Metrics

In literature, minimum square error (MSE), minimum absolute error (MAE), and root mean square error (RMSE) are generally used. These parameters, which are also generally used in machine learning studies, are also widely used and considered valid in wind energy forecasting (González-Sopeña et al., 2021; Karaman, 2023; Piotrowski et al., 2022).

3.2. Acceptable Error Development Ranges

Acceptable error limits in wind energy forecasts can vary depending on the methods used and data quality. While there is no consensus in the literature, each improvement appears to be valuable. Different studies have identified different levels of improvement. Error metric improvements, which generally range from 2% to 70%, vary depending on the baseline model used and the models compared with it (Piotrowski et al., 2022). It is known that small changes can make a significant difference in multivariate, multi-step ultra-short-term wind energy forecasting (Yang et al., 2024; Zhao & Bai, 2024). While any improvement is acceptable in forecasts based on the metrics, there are different ranges for significant progress. For example, studies using LSTM models for short-term wind speed forecasting report RMSE reductions of 7–30% compared to traditional ARIMA or SARIMA approaches, with close alignment of MAE improvements (R. Liu et al., 2018). Hu et al. (2021) proposed a hybrid short-term forecasting method that integrates smoothed numerical weather prediction models with a Gaussian process (GP) (S. Hu et al., 2021). Compared to the primary GP, forecast accuracy across different seasons was increased by 7.02% to 29.7%, 0.65% to 10.23%, and 10.88% to 37.49% using the smoothed numerical weather prediction, and 10.88% to 37.49% using the proposed hybrid model. Similarly, R^2 values above 0.91 are common in hybrid models, but these values change as time steps increase. While these rates reflect strong explanatory power in capturing nonlinear wind dynamics, performance degrades with error accumulation (Chandra et al., 2013; Kumar et al., 2024b). Hybrid models incorporating deep learning and optimization

techniques demonstrate the most significant error reduction performance in the literature. Kumar et al. (2024) report that hybrid frameworks achieve 25–51% RMSE improvements over baseline models in multi-step scenarios, outperforming simpler hybrids. Such improvements are critical for operational efficiency, as even marginal RMSE reductions (e.g., 3–5%) can improve grid stability and revenue in energy markets (Kumar et al., 2024b). Despite these gains, challenges persist as the number of steps in standardized benchmarks increases. Considering similar studies mentioned in previous sections, it can be observed that in the first step, average MAE and MSE, and RMSE-based error metric reductions fluctuate between 2% and 70%.

3.3. Importance of Hyperparameter Optimization

Numerous studies have demonstrated the significant impact of hyperparameter tuning on model performance. Feurer et al. (2015) showed that appropriate hyperparameter optimization can improve the performance of standard machine learning algorithms by 3–15% on various datasets (Feurer et al., 2015). Li et al. (2019) emphasized, hyperparameters such as learning rate can affect not only the speed of convergence but also whether the model converges (Li et al., 2019). Similarly, Goodfellow et al. (2016) emphasized that the success of deep learning applications often depends on the hyperparameter tuning rather than the choice of the algorithm itself (Goodfellow et al., 2016).

Optuna's main search function, the Tree-Structured Parzen Estimator, has been shown to outperform Grid Search and Random Search on many hyperparameter optimization problems (Falkner et al., 2018). Another important reason is its mechanism for stopping 'unnecessary' or inefficient trials. This approach is called the 'Pruning' mechanism. Almarzooq and Waheed (2024) showed that Optuna's pruning mechanisms can provide computational savings of up to 50% in the training of deep learning models (Almarzooq & Bin Waheed, 2024). Hanifi et al. (2024) compared Scikit-opt, Optuna, and Hyperopt for optimizing CNN and LSTM models and found that Optuna was the most efficient for both (Hanifi et al., 2024). Recently, Optuna has offered significant potential for advancement in the field of hyperparameter optimization. Its features, such as dynamic search space definition, efficient search algorithms, pruning mechanisms, and parallelization support, have made it a valuable tool for both researchers and practitioners.

4. CRITICAL ASSESSMENT AND RESEARCH GAPS

As a result of the literature review, the literature provides detailed information on ultra-short-term, multivariate, and multi-attribute forecasting, including noise reduction in ultra-short-term, performance and processing time reduction by improving feature selection, and dynamic time-aware and hybrid methods.

While numerous studies on ultra-short-term wind power forecasting have been published in the literature, an in-depth review of these studies reveals several limitations and unresolved issues. This section will discuss the strengths and weaknesses of existing studies and highlight gaps that will inform future research.

4.1. Data Quality and Missing Data

Data quality is one of the factors that most significantly impacts forecast performance. Measurement errors, sensor malfunctions, or incomplete observations in meteorological data negatively impact model accuracy. Many studies in the literature have attempted to address these issues with simple interpolation methods, but these approaches have proven inadequate in capturing sudden fluctuations. Advanced imputation methods have been proposed to overcome the limitations of simple interpolation techniques. The Generative Adversarial Imputation Networks (GAIN) method has shown superior performance compared to traditional approaches like ARMA in completing multidimensional meteorological data series (Popolizio et al., 2021). More advanced methods for completing missing data are needed. The Informed Similarity Transfer (IST) framework leverages spatial proximity, land cover similarity, and elevation differences to reconstruct incomplete datasets while preserving temporal patterns and spatial coherence (Meng et al., 2024). Spatiotemporal kriging has been effectively applied to impute missing data in chaotic time series for lightning prediction (Nystrom et al., 2023).

4.2. Model Complexity and Computational Load

While deep learning-based models provide high predictive accuracy, they incur significant computational costs when trained on large datasets. While deep learning models excel in complex tasks like image processing and human activity recognition, they often require significant computational resources (Jiang, 2025; Talnikar et al., 2025). This becomes a limiting factor in real-time applications. Studies focusing on computational efficiency alongside model performance are relatively scarce in the literature.

4.3. Generalizability Issue

Many models are trained with data specific to a specific region or a specific group of turbines. Consequently, these models fail to perform equally well when applied to different geographical conditions or across different time periods. This demonstrates the models' low generalizability. It is suggested that this limitation could be overcome in the future through methods such as transfer learning and domain adaptation. Sajol et al. (2024) introduced a deep domain adaptive approach for wind power prediction across different locations, achieving higher accuracy compared to traditional non-adaptive meth-

ods. These studies collectively highlight the potential of transfer learning and domain adaptation techniques to overcome the limitations of region-specific models, enabling more robust and generalizable wind turbine performance prediction and fault detection across diverse geographical conditions and time periods (Islam Sajol et al., 2024).

4.4. Lack of Interpretability

While deep learning-based models offer high performance, their “black box” nature makes explaining their decision-making mechanisms quite challenging. Because security and transparency are crucial in energy systems, the integration of interpretable AI approaches into the literature is a pressing need.

4.5. General Trends in Literature and Potential Research Areas

In recent years, hybrid models and optimization algorithms have gained prominence, and deep learning methods have become almost standard. However, most studies have been limited to experimental validation, and relatively few industrial-scale applications have been implemented. Furthermore, the integration of models with energy markets and their use in real-time decision support systems have not yet been sufficiently explored.

Furthermore, technological development processes such as Model Context Protocol and the integration of Generative Artificial Intelligence have not yet been incorporated into the game. This allows for numerous advancements, from maintenance and repair to improved electricity production forecasting. This field holds great potential as a significant research topic.

5. CONCLUSION AND RECOMMENDATIONS

The presented literature review reveals that ultra-short-term wind power forecasting plays a critical role in the reliability and sustainability of energy systems. Studies have demonstrated a wide range of methodological variation, evolving from traditional statistical methods to deep learning-based approaches. The use of hybrid models and optimization algorithms, in particular, has yielded promising results in improving forecast accuracy. Ultra-short-term wind power forecasting is not only an academic research area but also a strategic element that will shape the future of energy systems. Developments in the literature indicate that progress in this field will continue rapidly. However, filling existing gaps and developing next-generation methods will be possible through interdisciplinary collaborations and industry-academia partnerships.

However, a critical review of the literature also reveals several fundamental issues. Uncertainties related to data quality, high computational costs, lack of generalizability of models, and interpretability issues are among the prior-

ity areas that need to be addressed in the future.

Key Parts of Literature:

- Ultra-short-term forecasts are critical for maintaining the balance between energy supply and demand.
- Deep learning-based models demonstrate superior performance, particularly in capturing sudden fluctuations.
- Hybrid approaches combine the strengths of different methods to deliver more reliable forecasts.
- Data preprocessing, feature selection, and hyperparameter optimization are critical factors determining model success.

5.1. Recommendations

- ***Data Quality and Missing Data Management:*** More advanced missing data completion and noise reduction methods should be developed.
- ***Computational Efficiency:*** Lightweight models that consume less resources and are suitable for real-time applications should be designed.
- ***Generalizability:*** Models should be adapted to different geographical conditions using transfer learning and domain adaptation techniques.
- ***Interpretability:*** The transparency of model decisions should be increased through the integration of explanatory AI methods.
- ***Industrial Applications:*** Moving beyond academic research, models should be directly integrated with energy markets and grid management systems.

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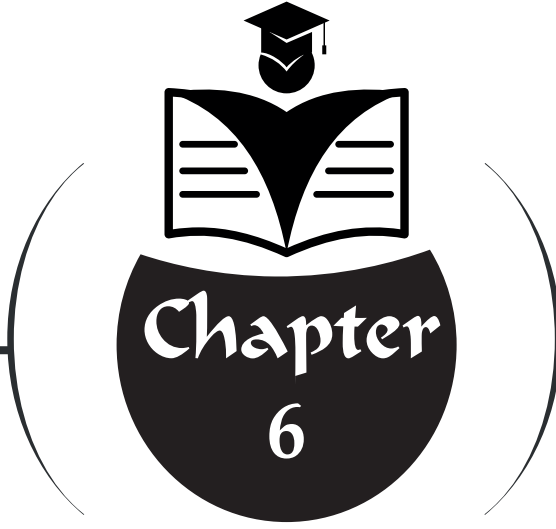
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ADVANCED THEORETICAL CONCEPTS IN DRYING TECHNOLOGY

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1. Foundations of Drying Technology

1.1 Introduction to Drying

Drying is an essential, and highly energy-intensive unit operation central to the production and preservation of materials across chemical, agricultural, pharmaceutical, and food industries (Yağcıoğlu, 1999). It is not merely a process of water removal but a finely controlled kinetic mechanism designed to minimize the free moisture content of a solid matrix. The ultimate goal is to reduce the material's water activity (a_w) below critical thresholds required to inhibit microbial growth, enzymatic browning, and undesirable chemical changes, thereby guaranteeing extended stability and shelf life (Troller, 1986).

From an engineering perspective, drying is an exercise in managing the simultaneous and coupled phenomena of heat and mass transfer (Heybeli & Ertekin, 2007). Energy must be transferred to the material to supply the latent heat of vaporization (λ) required for the phase change, and the resulting water vapor must be efficiently transported from the interior of the solid, through its structure, and into the surrounding drying medium. Inefficient drying not only consumes excessive energy (often accounting for a significant fraction of industrial energy use) but can also lead to severe product quality deterioration, including thermal damage, color loss, nutrient degradation, and structural defects (Atlı & Ötleş, 1999). Consequently, precise mathematical modeling of these mechanisms is non-negotiable for optimized industrial design and scale-up (Kiranoudis et al., 2015).

1.2 Thermodynamic Equilibrium and Moisture States

Thermodynamic equilibrium in the context of drying is the state reached when the vapor pressure of the water within the material is equal to the partial pressure of water vapor in the surrounding air. At this point, there is no net transfer of water between the material and the air, and drying stops. The thermodynamic state of water within the material dictates the energy barrier that must be overcome for its removal.

1.2.1 Moisture Classification and Water Activity

As drying progresses, the easier-to-remove unbound moisture leaves first (constant rate period), while the subsequent removal of bound moisture (falling rate period) requires increasingly more energy per unit mass of water, as the binding forces become dominant. Moisture in porous materials is classified based on the energy required for its removal relative to:

1. **Bound Moisture:** Water strongly held by the solid through physical adsorption to internal surfaces, chemisorption, or capillary forces within micro-pores. This water has a depressed vapor pressure compared to pure water, requiring higher energy input for vaporization. Its removal requires ener-

gy greater than the latent heat of vaporization for pure water, as additional energy must be supplied to break these strong binding forces.

2. Unbound (Free) Moisture: Water that behaves thermodynamically like bulk liquid water, typically residing in macro-capillaries or on the surface. Its removal defines the primary target of most commercial drying operations. Removing this water requires only the standard latent heat of vaporization for pure water.

The Equilibrium Moisture Content (X_e) is the final, steady-state moisture content at which the material is in perfect thermodynamic balance with the temperature and relative humidity of the surrounding air. At the net rate of water adsorption equals the net rate of water desorption. This condition is directly related to the ambient air's water activity, which is the principal thermodynamic driving force.

1.2.2 Sorption Isotherms and Model Fitting

Moisture Sorption Isotherms are indispensable thermodynamic curves, plotting Equilibrium Moisture Content versus material's water activity at a constant temperature. These curves are critical for predicting storage stability, calculating drying energy requirements, and designing moisture barrier packaging (Mohamed et al., 2023). They define the hygroscopic properties of a material, showing how much moisture it will gain (adsorption) or lose (desorption) until it reaches thermodynamic equilibrium with the environment.

Several theoretical and semi-empirical models are used to fit and interpret isotherm data:

- BET (Brunauer-Emmett-Teller) Model: A kinetic theory based on multilayer adsorption, primarily used to estimate the monolayer moisture content, representing the maximum amount of water that is most tightly bound to the primary adsorption sites on the solid surface (Al-Muhtaseb et al., 2016).
- GAB (Guggenheim-Anderson-de Boer) Model: A modification and extension of the BET theory, generally providing the best fit for food products across the widest range of water activities. Its parameters provide insights into the binding energy of the monolayer and subsequent adsorbed layers.

1.2.3 Net Isosteric Heat of Sorption

The Net Isosteric Heat of Sorption (Q_{st}) quantifies the energy required to vaporize adsorbed water, measured as the excess energy above the latent heat of vaporization of pure water. It directly reflects the strength of the attractive bonds (van der Waals, hydrogen bonds) between water molecules and the hydrophilic components of the solid matrix (Sjøgård & Hansen, 2022).

Q_{st} is determined by applying the Clausius-Clapeyron Equation to isotherm data obtained at various temperatures. Crucially, Q_{st} is a strong function of moisture content: it increases exponentially as X_e decreases. This thermodynamic reality dictates that removing the final trace amounts of water is disproportionately energy-intensive, as only the most highly-bound water molecules remain (Lahsasni et al., 2005).

2. Kinetic Analysis and Mathematical Modeling of Drying

Kinetic analysis and mathematical modeling of drying are essential tools used to understand, predict, optimize, and scale-up the drying processes for various materials, particularly agricultural and food products. Drying kinetics focuses on the rate of moisture removal, which is fundamentally controlled by the balance between external surface evaporation and internal moisture transport.

2.1 The Characteristic Drying Curve

The drying process is universally characterized by a graph of the drying rate (dX/dt) versus the average moisture content (X) of the material. This curve reveals the shifting rate-limiting mechanisms.

2.1.1 Constant Rate Period (CRP): External Control

The CRP occurs after a brief initial adjustment period and is characterized by a maximal and constant drying rate.

- Mechanism: The surface of the material remains fully saturated with water, behaving identically to a free liquid surface. Internal mass transfer (moisture movement) is rapid enough to continuously replenish the surface moisture lost by evaporation.
- Rate Control: The drying rate is governed solely by external factors: the rate of convective heat transfer from the drying air to the surface and the external mass transfer of vapor away from the boundary layer. The surface temperature remains stable at the wet-bulb temperature of the drying air (Yağcıoğlu, 1999).
- Termination: The CRP ends at the Critical Moisture Content, the point where dry spots begin to form on the surface, and the rate of internal moisture movement becomes the dominant, limiting factor (Heybeli & Ertekin, 2007).

2.1.2 Falling Rate Period (FRP): Internal Control

The FRP commences at Critical Moisture Content and typically constitutes the majority of the drying time, particularly for porous and hygroscopic materials.

- **Mechanism:** The drying rate declines continuously because internal moisture transport to the surface is insufficient to sustain saturation. The effective evaporation plane recedes into the interior of the solid, meaning that water vapor must now diffuse through the material's pore structure to reach the surface.

- **Rate Control:** The process is governed by internal factors, primarily the mechanisms of mass transfer, which include:

- **Capillary Flow:** Dominant at higher moisture contents, driven by surface tension gradients.

- **Liquid Diffusion:** Driven by concentration gradients in hygroscopic materials.

- **Vapor Diffusion:** Driven by partial pressure gradients through air-filled pores, crucial at low moisture contents (Mwithiga & Olwal, 2007).

2.2 Equations for Mass Transfer

2.2.1 Empirical Kinetic Models

Simple, integrated models are often used to fit the relationship between Moisture Ratio and time during the FRP, categorized as thin-layer models:

$$MR = \frac{X - X_e}{X_0 - X_e}$$

- **Lewis Model:** The simplest first-order analogy: $MR = \exp(-kt)$
- **Page Model:** A widely recognized improvement that often provides a better fit for biological materials: $MR = \exp(-kt^n)$

These models, while practical, are phenomenological; their parameters are conditional fitting constants that lack direct physical meaning regarding the underlying transport mechanisms (Doymaz & İsmail, 2012).

2.2.2 Fick's Second Law and Effective Diffusivity

For a robust, physics-based description of internal, concentration-driven moisture movement (liquid diffusion), Fick's Second Law is universally employed:

The Effective Moisture Diffusivity (D_{eff}) (units of m^2/s) is an adjustable lumped parameter that attempts to incorporate all complex internal mass transfer mechanisms (diffusion, capillary flow, thermal effects) into a single measurable value. Solving this partial differential equation for simple geometries (e.g., infinite slab) yields a solution often simplified to the first term of the series:

$$MR = \frac{8}{\pi^2} \exp\left(-\frac{\pi^2 D_{eff} t}{4L^2}\right)$$

This simplification allows to be determined from the slope of $\ln(MR)$ versus time (t). However, this method assumes is constant, an assumption that frequently breaks down in industrial drying processes where temperature and moisture gradients are significant (Mwithiga & Olwal, 2007).

2.2.3 The Arrhenius Relationship and Activation Energy

To quantify the fundamental dependence of mass transfer on temperature, the relationship between D_{eff} and absolute temperature is described by the Arrhenius Equation:

$$D_{eff} = D_0 \exp\left(-\frac{E_a}{RT}\right)$$

Plotting $\ln(D_{eff})$ against $1/T$ yields a straight line whose slope is directly proportional to the Activation Energy (E_a) (Zare & Chen, 2009). E_a is the minimum energy barrier that must be overcome for the internal moisture diffusion process to be activated. A lower value signifies that the moisture in the material is less tightly bound and/or the diffusion pathway is less tortuous, making the drying process less sensitive to temperature variations and more energy-efficient (Geng et al., 2009).

3. Mechanisms and Engineering of Advanced Drying Systems

Modern drying technology aims to overcome the intrinsic limitations of single-mode operations, primarily the slow rate and thermal degradation associated with the FRP.

3.1 Convective Drying

Convective drying is a mass and heat transfer process where hot, dry air or gas is circulated around a material to remove moisture. This method is the most common industrial drying technique, relying on the principle of convection to transfer heat and accelerate evaporation. Convective drying is the standard, utilizing a heated fluid (typically air) to transfer energy via convection to the material surface. The drying rate is critically influenced by several key factors. Air Temperature is essential, as a higher temperature accelerates drying by increasing the rate of heat transfer and creating a greater vapor pressure difference between the material and the air. Similarly, Air Velocity is crucial; faster airflow enhances both convective heat and mass transfer, effectively carrying away evaporated moisture and boosting the drying speed. The capacity of the air to absorb moisture is determined by Air Humidity; lower relative humidity is desirable because it promotes faster evaporation. Finally, Material Properties such as thickness, particle size, and porosity dictate how moisture moves from the interior of the material to its surface, thus controlling the overall drying rate.

3.1.1 Convection, Conduction, and Boundary Layer Effects

- **Heat Transfer:** High air velocity reduces the aerodynamic boundary layer thickness, thereby increasing the convective heat transfer coefficient (h) and accelerating the CRP.
- **Mass Transfer:** The moisture vapor is removed by the moving air, a process also enhanced by increased air velocity (increased mass transfer coefficient).
- **Limitation:** Despite high external transfer rates, the process relies on slow heat conduction from the surface to the interior and slow diffusion of liquid/vapor moisture from the interior to the surface during the FRP.

3.1.2 Quality Degradation and Case Hardening

The long exposure times inherent in the FRP under convective drying lead to critical defects:

- **Thermal Degradation:** Extended exposure to high surface temperatures causes significant loss of heat-sensitive nutrients (e.g., Vitamin C) and desirable pigments (Atlı & Ötleş, 1999).
- **Case Hardening:** Rapid initial evaporation causes the formation of a dense, low-porosity, and relatively impermeable layer on the surface. This crust severely restricts the subsequent movement of internal moisture, exacerbating the slow rate of the FRP and often leading to high internal residual moisture (Amit et al., 2017).

3.2 Microwave Drying

Microwave drying is a rapid dehydration technique that uses electromagnetic waves in the microwave frequency range to remove moisture from materials. Unlike conventional methods that heat the surface and rely on conduction, microwave drying employs volumetric heating, where the energy is absorbed directly by the polar molecules (primarily water) within the material. Microwave drying fundamentally transforms the heating mechanism from external to internal (volumetric heating). Microwave drying is a revolutionary dehydration technique that leverages electromagnetic waves to achieve volumetric heating, setting it apart from conventional surface-heating methods. The process begins with dielectric heating: as water molecules, which are electric dipoles, are exposed to the microwave's alternating electric field, they undergo billions of rapid molecular oscillations per second. This rapid movement creates intense intermolecular friction, generating thermal energy (heat) directly inside the material. Crucially, this internal heating causes water to vaporize rapidly, building a high vapor pressure gradient that drives moisture out from the interior to the surface. This "drying from the in-

side out" mechanism is what dramatically reduces processing time, enhances energy efficiency by selectively heating water, and ensures superior product quality by minimizing thermal degradation and case hardening. These advantages, combined with better uniformity and an inherent bactericidal effect, make microwave drying highly valuable for applications requiring rapid, high-quality, and safe dehydration.

3.2.1 Mechanism of Dielectric Energy Absorption

Microwave energy is coupled directly into the material through the interaction of the electromagnetic field with the polar water molecules. Two primary mechanisms drive internal heat generation:

1. Dipolar Rotation: Polar water molecules rapidly rotate to align with the oscillating electric field, generating heat via molecular friction.
2. Ionic Conduction: Dissolved ions move in the oscillating field, colliding with surrounding material and generating heat.

The power absorbed is a function of the electric field strength and the material's dielectric loss factor: Since is strongly dependent on moisture content and temperature, heating is non-linear and highly selective to high-moisture regions.

3.2.2 Kinetic Advantages and Control Challenges

- Kinetic Advantage: Internal heating creates a high internal vapor pressure and often results in a reverse temperature gradient (core hotter than surface). This powerful internal pressure gradient becomes the dominant mass transfer driving force, substantially accelerating the rate-limiting FRP (Sarimeseli, 2011).
- Structural Effects: The rapid internal vaporization often causes a "puffing" effect, increasing the final product's porosity and, consequently, improving its rehydration capacity.
- Control Challenges: Microwave power must be carefully modulated because the material's dielectric properties change rapidly as moisture is removed. Uneven energy distribution can lead to non-uniform drying and localized **thermal runaway** (hot spots), causing severe thermal damage to parts of the product.

3.3 Hybrid Drying Technologies

Hybrid systems combine energy sources to create synergistic effects that surpass the limitations of single methods. Microwave-Assisted Convective Drying (MACD) combines the external boundary layer control of hot air with the internal volumetric drive of microwave energy (Gedik et al., 2025)

- **Synergy:** Hot air handles the surface evaporation and rapidly removes the released vapor, preventing saturation. Microwave energy, applied simultaneously or intermittently, constantly maintains a high internal pressure gradient to overcome the internal diffusion barrier of the FRP.
- **Performance:** MACD has been shown to reduce total drying time by up to 90% compared to pure convective drying, while the rapid processing time leads to demonstrably better retention of heat-sensitive compounds and reduced energy consumption per unit of water removed (Garba & Kaur, 2014).

3.4 Pre-treatment and Post-treatment

Pre-treatments are critical steps applied before the main drying operation to fundamentally alter the material's physicochemical structure. The goal is two-fold: accelerating the drying process (enhancing mass transfer) and preserving or enhancing desirable quality attributes (e.g., color, texture, nutritional value). These methods often work by either modifying cell membrane permeability or inactivating detrimental enzymes.

3.4.1. Chemical Pre-treatments

Chemical immersion treatments are designed to stabilize the product matrix.

- **Enzyme Inactivation and Color Stability:** Treatments using Citric Acid or Ascorbic Acid are classic examples used to combat enzymatic browning, a common quality defect in sliced fruits like apples and carrots. These acidic environments inhibit the activity of the polyphenol oxidase (PPO) enzyme (Atlı & Ötleş, 1999). PPO activity typically decreases sharply below a pH of 3.5-4.0, which the acid treatment achieves.

- **Permeability and Diffusivity Enhancement:** The low pH and the osmotic pressure differences created during chemical immersion can also slightly weaken the cell wall and membrane structure, a phenomenon known as plasmolysis. This structural change theoretically increases the porosity and permeability of the cell network. As a result, the internal resistance to moisture movement is lowered, directly increasing the calculated Effective Moisture Diffusivity (D_{eff}) during the subsequent thermal drying stage, thus accelerating the process (Garba & Kaur, 2014).

3.4.2. Thermal Pre-treatments (Blanching)

Blanching involves brief exposure to high heat (hot water or steam). While primarily known for enzyme inactivation, its impact on the material structure is significant:

- **Tissue Softening and Resistance Reduction:** Blanching denatures proteins and degrades pectic substances that hold the cell structure rigid. This soft-

tening of the tissue structure leads to a reduction in the internal mass transfer resistance. The path for liquid water movement is less tortuous, which enhances water removal, especially in the Falling Rate Period (Garba & Kaur, 2014).

- **PPO and Peroxidase Inactivation:** Thermal energy permanently denatures the PPO enzyme, and often the more heat-resistant peroxidase enzyme, thereby stabilizing the product color and flavor compounds.

3.4.3. The Concept of Rehydration and Quality Assessment

Rehydration capacity is a crucial quality indicator for dried food products, serving as a measure of the extent of irreversible structural damage caused by the drying process.

The goal of ideal drying is to remove water without altering the solid matrix structure. However, in reality, the withdrawal of water creates large capillary tension forces that cause cells to collapse, leading to shrinkage and densification of the material.

- **Mechanism:** Good rehydration capacity indicates that the material successfully retained its porous, open-cell structure during drying. When placed back in water, the open pores allow rapid capillary action, enabling the material to regain moisture and swell back to a volume approaching its original state.

- **Rehydration Ratio (RR):** The rehydration ratio is the primary metric used to quantify this quality:

$$RR = \frac{\text{Mass of Rehydrated Product}}{\text{Mass of Dry Product}}$$

- **Interpretation:** A higher RR value indicates superior quality, suggesting that the chosen drying method (e.g., hybrid methods like MACD, which minimize shrinkage) successfully maintained the structural integrity and high porosity of the material. Conversely, a low RR signifies severe structural collapse (case hardening, excessive densification) occurred during drying, resulting in a low final water-holding capacity (Doymaz & İsmail, 2012)

4. Classification of Dryers

Drying equipment is broadly classified based on the mode of operation (Batch or Continuous) and mode of heat transfer.

4.1. Mode of Operation

This categorizes dryers based on how the material is handled through the drying process:

4.1.1 Batch Dryers

The material is loaded, dried for a set period, and then unloaded. Common types of batch dryers are; tray dryer, batch fluidized bed dryer, vacuum dryer etc. The fundamental operation of a batch dryer involves three distinct phases that are repeated for every batch (Jokiniemi & Ahokas, 2014):

- **Loading:** The wet material (such as grains, powders, pastes, or fabricated goods) is loaded into the drying chamber or onto trays/shelves inside the dryer.
- **Drying:** A heating medium (typically hot air or a heated contact surface) is introduced to the chamber. Temperature and airflow are precisely controlled to promote the evaporation of moisture from the material. This phase runs for a specific duration until the material reaches the desired final moisture content. In some designs (like recirculating grain dryers), the material may be constantly mixed or cycled to ensure uniform drying.
- **Unloading:** Once the material is dry, the dryer's operation stops, and the entire batch is removed before a new one can be loaded.

4.1.2 Continuous Dryers

A continuous dryer is a type of industrial equipment designed to remove moisture from a constant, uninterrupted flow of material. Wet material is continuously fed into the dryer at one end, and dried material is continuously discharged from the other, making it ideal for large-scale, high-capacity production. The material continuously flows through the dryer. Common types of continuous dryers are; spray dryer, rotary dryer, tunnel dryer etc. The general principle involves transporting the material through a heated chamber where moisture is removed, typically through convection.

- **Feeding:** An automatic feeder, such as a conveyor, evenly distributes the wet material onto the transport mechanism (e.g., a mesh belt, rotary drum, or vertical column).
- **Transport and Drying:** The material is conveyed continuously through the drying chamber. Hot air (or another drying medium) is circulated through or over the material. The heat causes the moisture to evaporate. Continuous dryers often employ multiple drying zones with controlled parameters (temperature, airflow, and humidity) to optimize the drying rate as the material's moisture content decreases.
- **Moisture Removal:** Fans and exhaust systems remove the moisture-laden air (water vapor) from the chamber.
- **Discharging:** The completely dried product is automatically discharged from the system, ready for downstream processing or packaging.

4.2 Mode of Heat Transfer

This is the most fundamental classification, determining how the necessary heat for evaporation is supplied to the wet material:

4.2.1 Direct (Convective) Dryers:

Heat is transferred by direct contact between the wet solid and a hot gas (usually air). The hot gas also serves to carry away the evaporated moisture. The principle of direct drying is based on convective heat transfer and simultaneous mass transfer:

- Heat Transfer: The hot gas (or drying medium) flows over and/or through the wet material, transferring its thermal energy via convection.
- Moisture Vaporization: This heat raises the temperature of the water (moisture) in the material, causing it to vaporize into steam.
- Mass Transfer: The moving gas stream then sweeps away the water vapor, removing the moisture from the system.

4.2.2 Indirect (Contact or Conductive) Dryers:

Heat is transferred by conduction through a metal wall that separates the heating medium (like steam, hot oil, or electricity) from the wet material. This method prevents product contamination by combustion gases. The fundamental principle is conduction heat transfer (Raouzeos, 2003).

- A heating medium (e.g., steam, thermal oil, hot water, or hot combustion gas) circulates through an enclosed space, such as a jacket, drum wall, hollow paddle, or tube bank.
- The heat is transferred from the heating medium, through the solid metal wall of the dryer vessel or contact surface, to the wet material that is in physical contact with that surface.
- The heat absorbed by the wet material causes the moisture (water or solvent) to evaporate.
- The evaporated vapor is then typically removed by a small flow of purge gas (often inert) or by maintaining the dryer chamber under a vacuum (lowering the boiling point).

4.2.3 Radiant Dryers:

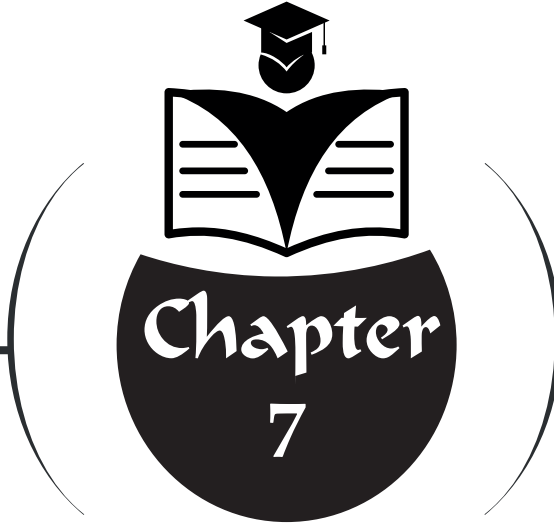
Heat is transferred primarily by radiation (electromagnetic waves). Unlike conventional dryers that heat the air (convection) or a surface the product rests on (conduction), radiant dryers transfer heat directly to the material.

- **Radiation Generation:** Infrared heaters (typically electric resistance elements, ceramic, quartz, halogen, or natural gas burners) generate infrared radiation.
- **Absorption and Conversion:** The product's surface absorbs this electromagnetic radiation, which then penetrates into the material. The energy is converted into heat upon absorption.
- **Moisture Evaporation:** This direct and rapid internal heating raises the material's temperature quickly, causing the internal moisture to evaporate much faster than in conventional methods.
- **Airflow (in some designs):** Many industrial IR dryers incorporate an air circulation system to remove the evaporated moisture and prevent overheating, often combining the efficiency of radiant heating with the moisture-removal capability of convective drying.

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A PLM-BASED FRAMEWORK FOR MISSION PLANNING AND DATA INTEGRATION IN UNMANNED AERIAL VEHICLES: A WATER MONITORING CASE STUDY

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1. Introduction

Unmanned aerial vehicles, or UAVs, are now widely used in a variety of fields, including military reconnaissance, agricultural monitoring, environmental observation, and disaster management (Gupta et al., 2013; Chen et al., 2025). Modern UAV systems are expected to perform well in mission efficiency, environmental compliance, and data management in addition to being able to fly. Systematic, traceable, and data-driven planning is essential in situations where missions are frequent, repetitive, and require ongoing monitoring (Ore et al., 2015; Rezk et al., 2023).

In addition to product design and manufacturing, Product Lifecycle Management (PLM) provides a comprehensive infrastructure for operational processes like mission definition, constraint validation, environmental monitoring, post-flight evaluation, and mission reuse (Ameri & Dutta, 2005; Kiritis, 2011). According to earlier studies, PLM environments like Aras Innovator can be tailored for aerospace applications, allowing for lifecycle traceability and structured UAV repositories (Bernabei et al., 2014; NATO, 2012). A methodological basis for integrating lifecycle management into UAV operations is also offered by model-based approaches for requirement representation in PLM (Yaman, 2020). Few studies, nevertheless, have demonstrated how PLM can be operationalized to combine environmental data collection, regulatory constraints, and real-world UAV missions.

By offering a PLM-based framework for UAV mission planning and data integration that was created and tested on the open-source Aras Innovator platform, this chapter fills that knowledge gap. The framework uses an Item-Relationship-Item structure to digitally model UAV platforms, payloads, missions, and collected data. Prior to deployment, automated assessments of mission viability are conducted, encompassing endurance, payload capacity, and firmware compliance. During execution, environmental parameters such as water pH, temperature, and dissolved oxygen are captured by onboard sensors, transmitted through the UAV's onboard computer via a REST-based service layer, and integrated into the PLM system. This architecture ensures that collected data are securely ingested, contextually linked to their originating mission and platform, and preserved for traceability and post-mission analysis.

The contributions of this chapter are threefold. First, a practical PLM data model for UAV mission management is proposed, where platforms, payloads, missions, and collected data are represented as interrelated digital items. Second, an integration architecture based on a lightweight REST interface is implemented to enable real-time ingestion of mission data into PLM. Third, the framework is validated through a freshwater quality monitoring mission,

demonstrating how PLM enhances safety, transparency, and decision-making by closing the loop from planning through execution to post-mission review.

The remainder of this chapter is organized as follows. Section 2 introduces the PLM modeling of UAV platforms within Aras Innovator. Section 3 describes the mission planning process with physical, operational, environmental, and regulatory constraints. Section 4 details the REST-based data integration architecture. Section 5 demonstrates mission planning, execution, and monitoring in Aras Innovator including post-mission data analysis and traceability. Finally, Section 6 summarizes the findings and highlights benefits.

2. Creating a UAV Platform in the Aras PLM Environment

2.1 Overall System Architecture

UAV operations in the proposed framework are represented through a three-tier architecture—edge, platform, and business—adapted from the Industrial Internet Reference Architecture (IIC, 2015) and customized for UAV mission management and environmental monitoring.

- **Edge tier** integrates the UAV's physical assets (airframe, rotors, battery), onboard sensors such as water quality, flight controller, battery health, and the onboard computer. This layer collects and preprocesses flight and environmental data, executes low-level control tasks such as path adjustments and health checks, and serves as the communication gateway to higher tiers.

- **Platform tier** provides the virtual representation of UAVs within the PLM system through a structured data repository. Both static data such as UAV configurations, payloads, mission records) and dynamic data streams collected during operations are managed here. An analytics layer processes these datasets, enabling dashboards, alarms, and notifications for mission monitoring and decision support.

- **Business tier** connects UAV data and analytics with domain-specific applications such as mission configuration, specialized UAV design, and predictive maintenance. This ensures that operational insights are systematically linked back to engineering data and maintenance actions, thereby closing the loop within the PLM framework.

Reliable UAV communication links, a key enabler for data exchange between tiers, have been surveyed extensively in recent literature (Gu & Zhang, 2023). This tiered architecture ensures that UAV operations are not only executed but also systematically captured, analyzed, and reintegrated into lifecycle management. By combining UAV data repositories, analytics, and predictive maintenance tools, the system supports both real-time operational control and long-term knowledge reuse. Communication between tiers relies on lightweight REST-based services, secured with TLS encryption and sche-

ma validation, as described in Section 4. This integration ensures that sensor observations, mission metadata, and operational logs are transmitted reliably from the edge to the PLM repository, preserving traceability throughout the mission lifecycle.

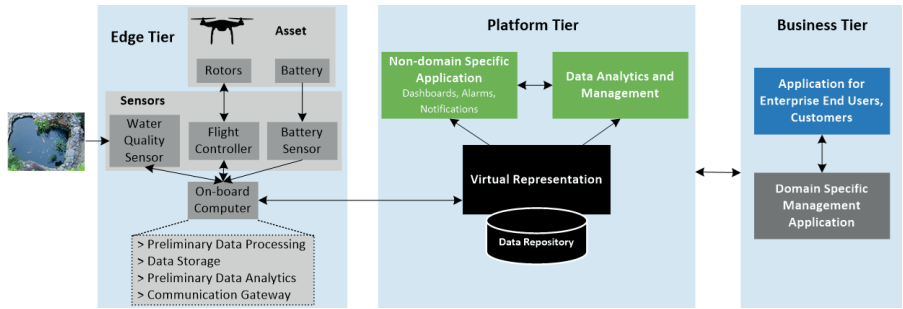


Figure 1. Overall system architecture of the UAV-PLM framework

2.2 PLM-Based Modeling of UAV Platforms

Aras Innovator is a web-based PLM platform designed around a service-oriented architecture (SOA). Its fundamental data model is the Item-Relationship-Item structure, in which every object is treated as an Item and associations between objects are captured as Relationships. Items are instances of ItemTypes, each identified by a 32-character globally unique identifier (GUID). RelationshipTypes define the source (parent) item, the related (child) item, and the relationship itself. This flexible structure enables consistent modeling of complex systems such as UAV platforms and missions.

As illustrated in Figure 2, the Item-Relationship-Item model organizes each element with identifiers, properties, and methods, while relationships provide the connective logic across the PLM repository. This structure underpins the way UAV components, mission records, and sensor data are represented in the system.

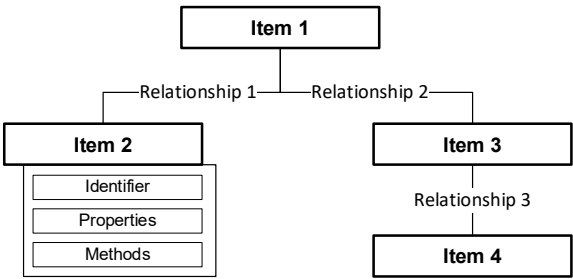


Figure 2. The Item-Relationship-Item structure in Aras Innovator PLM

Building on this foundation, UAV platforms and missions are instantiated as digital objects in PLM. Each UAV platform is represented as a top-level Item, with linked subcomponents including:

- Frame (airframe, motors, propellers)
- Power unit (battery and endurance estimation)
- Flight controller (model, firmware version)
- Payload (cameras, sensors, transmitters)
- Missions (historical and ongoing)
- Maintenance and calibration logs

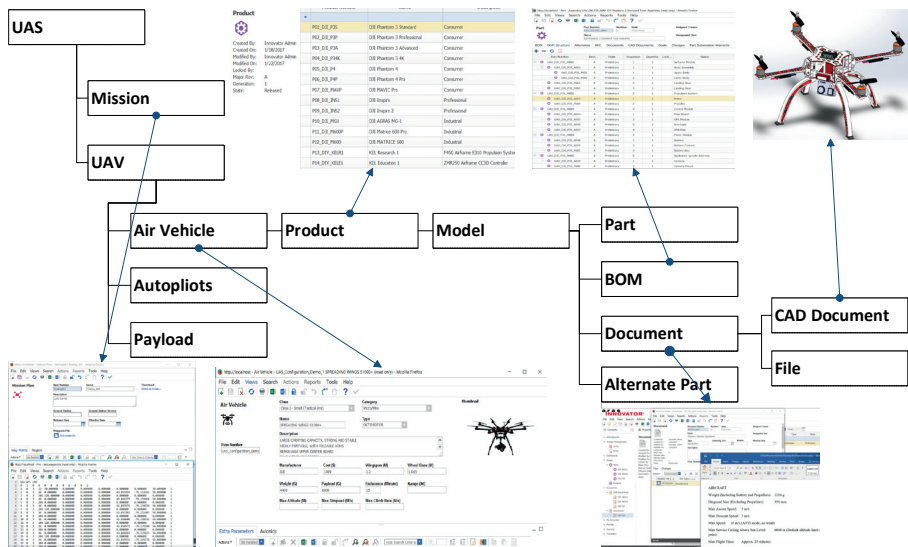


Figure 3. Customized UAS Data Repository in PLM System

A customized UAV data repository was developed in Aras Innovator to capture these relationships, aligning with established aerospace standards such as NATO STANAG 4586. As shown in Figure 3, the repository integrates UAVs, missions, payloads, and subsystems with related product data such as bills of materials (BOMs), CAD documents, specifications, and mission applications. Currently, six UAV configurations have been modeled in the repository: Flame Wheel 450 (two setups), DJI Phantom 3 Standard, ZMR 250, Parrot Bebo 2, and DJI S1000+.

This repository structure not only enables lifecycle traceability but also supports both traditional product development techniques (e.g., CAX, DFX)

and advanced analytics. By digitally linking UAV platforms, mission data, and sensor outputs through the Item-Relationship-Item paradigm, the PLM environment provides a robust foundation for mission planning, validation, and post-mission analysis. The role of this modeling in supporting operational requirements and constraint validation is further detailed in Section 3.

2.2.1 UAV Assembly and Bill of Materials

A critical element of UAV mission management in PLM is the digital representation of the UAV assembly and its bill of materials (BOM). The PLM system can manage configurations, verify mission viability, and guarantee that each mission is associated with the precise platform variant that carried it out by organizing the UAV at the component level.

The UAV assembly is modeled in Aras Innovator with hierarchical Items corresponding to the main subsystems:

- **Airframe:** frame, arms, and structural components.
- **Propulsion system:** motors, propellers, and electronic speed controllers (ESCs).
- **Power unit:** batteries and power distribution board.
- **Flight controller:** autopilot hardware such as Pixhawk, firmware version, and accelerometer/gyroscope modules.
- **Payload:** mission-specific sensors such as water quality probes, cameras, or communication modules.
- **Auxiliary subsystems:** telemetry radios, GPS, and ground communication devices.

Each subsystem is represented as a Part Item in PLM and linked to associated CAD documents, specifications, and mission application records. The BOM structure provides not only a record of the physical configuration but also an anchor for mission data, maintenance logs, and calibration history. Table 1 illustrates a sample BOM for a multirotor UAV used in freshwater monitoring.

This digital BOM ensures that every mission plan and its results are linked to the precise UAV configuration that was deployed. By anchoring operational data to verified hardware and software states, PLM supports traceability, configuration control, and reliable mission reuse. Section 2.3 builds on this assembly model by showing how UAV subsystems are linked with PLM functions to enable automated validation of endurance, payload capacity, and firmware compliance.

Table 1. Sample Bill of Materials for UAV Assembly

Subsystem	Component	Example Specification	Linked PLM Data
Airframe	DJI Flame Wheel 450 frame	Carbon fiber, 450 mm diagonal	CAD model, structural spec
Propulsion system	Brushless motors (x4)	920 KV, 10-inch propellers	Motor datasheet, test logs
Power unit	Li-Po battery	4S 5200 mAh, 25C	Battery spec, endurance record
Flight controller	Pixhawk autopilot	Firmware v4.2, MPU-6000 IMU	Firmware files, calibration data
Payload	Water quality sensor	pH 0-14, DO 0-20 mg/L, Temp 0-50 °C	Sensor spec, calibration logs
Communication	Telemetry radio + GPS	915 MHz, Ublox NEO-M8N	Config file, mission logs

2.3 Linking UAV Subsystems with PLM Functions

The Item-Relationship-Item data structure in Aras Innovator supports not only the digital storage of UAV components but also pre-mission validation of critical system requirements. Before mission release, the PLM environment automatically performs the following checks:

- **Endurance vs mission duration:** verifies whether available flight time, based on battery capacity and estimated power consumption, is sufficient to complete the planned mission.
- **Payload weight vs capacity:** ensures that the combined payload of sensors or cameras does not exceed the UAV’s maximum carrying capacity.
- **Firmware/software compliance:** confirms that the flight-controller firmware and mission-related software versions are up to date and compatible with operational constraints.
- **Maintenance records:** checks whether any subsystem requires calibration, inspection, or replacement before deployment.

These checks are enforced through PLM workflow states and server-side validation rules. As illustrated in Figure 4, the UAV platform integrates several critical subsystems, including the flight controller, onboard computer, propulsion system, airframe, and mission payloads such as water-quality sensors. The onboard computer functions as the central hub, receiving validated mission plans from the PLM environment, executing flight control and data-collection tasks, and communicating with the flight controller. For reliable operations, communication is bidirectional: the onboard computer reads telemetry (position, battery life, velocity, attitude) and sends commands to

maneuver the UAV according to the mission plan.

During flight, environmental data are collected through onboard sensors and transmitted back to the PLM repository, where they are linked to the originating mission and UAV configuration. This integration creates end-to-end traceability: each mission record in PLM is associated with the exact UAV configuration, firmware version, and sensor calibration files, ensuring that post-mission analysis is grounded in verified hardware and software states.

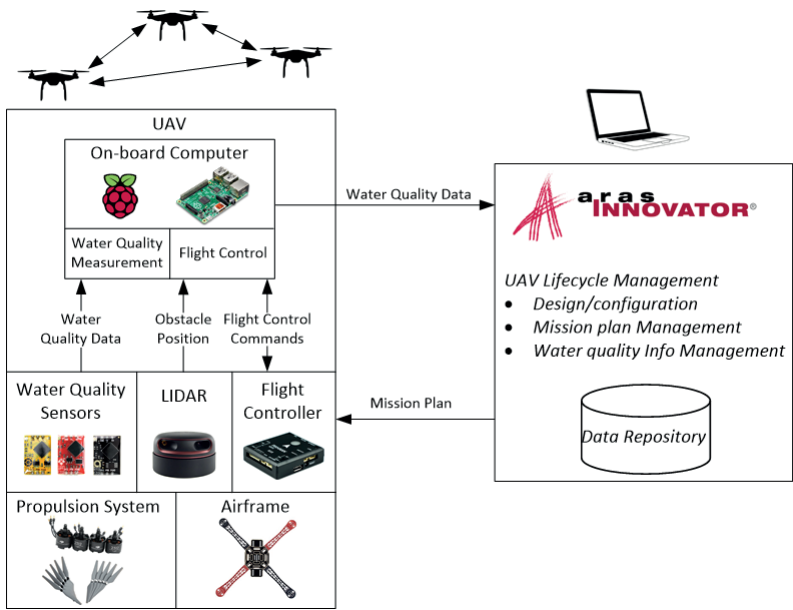


Figure 4. *Implemented system architecture linking UAV subsystems with the PLM environment.*

By connecting UAV subsystems with PLM functions, the architecture ensures that operational readiness is systematically assessed and that constraint violations are flagged before deployment. With UAV configurations, payload capacities, and subsystem states digitally modeled, Aras Innovator enforces pre-mission validation and guarantees lifecycle traceability. This linkage also enables mission reuse under version control, allowing operators to update waypoints or repeat missions under comparable conditions. Building on this digital foundation, the next step is to formalize how missions are planned and validated against physical, environmental, and regulatory constraints.

3. Mission Planning Process: Requirements and Constraints

3.1 Mission-Oriented Planning Approach

The success of UAV missions depends not only on flight capability but also on the precise definition of mission objectives, the suitability of environmental conditions, and the adequacy of the carrier platform. Mission planning must therefore extend beyond simple route or waypoint selection and incorporate multi-dimensional constraints such as endurance, payload, environmental conditions, and regulatory compliance (Gao et al., 2025).

The mission scenario considered is freshwater quality monitoring, where the UAV collects measurements of water temperature, pH, and dissolved oxygen at predefined coordinates. This type of mission requires careful planning to balance flight endurance with reliable data acquisition, ensuring both safety and traceability throughout the mission lifecycle.

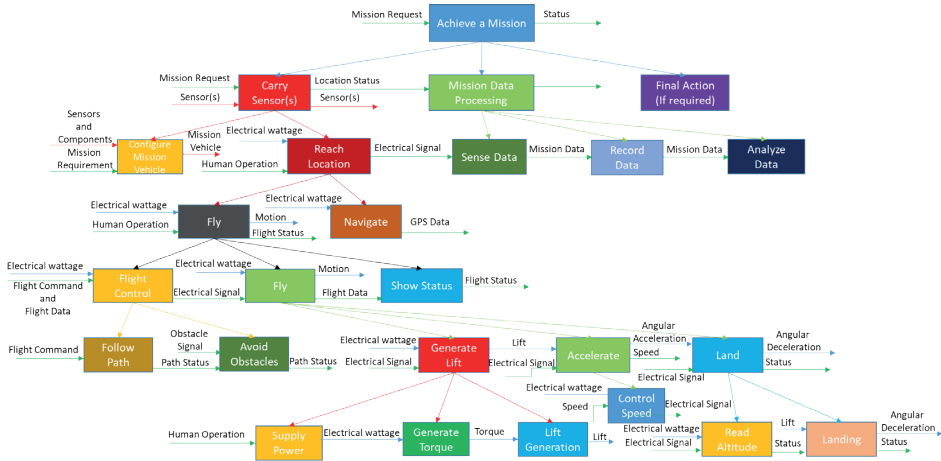


Figure 5. UAV mission activity flow illustrating hierarchical relationships between high-level objectives, operational tasks, and subsystem actions ensuring mission feasibility.

Figure 5 illustrates the hierarchical flow of UAV mission activities, beginning with high-level objectives such as accomplishing a mission and cascading through intermediate functions (carrying sensors, reaching designated locations, sensing and recording data) down to low-level physical actions (generating lift, controlling speed, supplying power). By structuring missions in this way, PLM can link each operational activity to the relevant subsystem and validation step, enabling systematic monitoring of constraints and ensuring mission feasibility.

3.2 Mission Attributes and Operational Requirements

Within the PLM environment, each mission is represented as a structured digital object that captures the parameters necessary for feasibility assessment, execution, and traceability. A mission record typically includes: the mission objective, the designated region of interest, waypoint coordinates, payload requirements, assigned UAV platform, operator information, and scheduling details. By storing these attributes in PLM, missions become governed entities that can be validated, versioned, and reused.

For the freshwater quality monitoring case study, several core operational requirements are defined: the UAV must provide at least 20 minutes of flight endurance; safe autonomous operation within a 2 km radius; payload capacity sufficient to carry sensors for pH, dissolved oxygen, and temperature measurement; and GPS-based waypoint tracking to ensure precise sampling. These requirements serve as minimum feasibility thresholds and are modeled directly in PLM as mission attributes.

Before deployment, the PLM environment automatically validates these mission attributes against UAV platform specifications and subsystem states. For example, if battery endurance is insufficient, if payload weight exceeds capacity, or if calibration records are outdated, the mission will not pass validation. By enforcing these operational requirements digitally, PLM ensures that only feasible and compliant missions are released for execution.

3.3 PLM-Based Management of Environmental Constraints

Environmental conditions directly influence both the safety of UAV operations and the quality of collected data. In the proposed framework, these conditions are formalized as rule-based constraints within the PLM environment. During mission definition, the PLM system queries external meteorological data providers and stores the results as structured items in Aras Innovator.

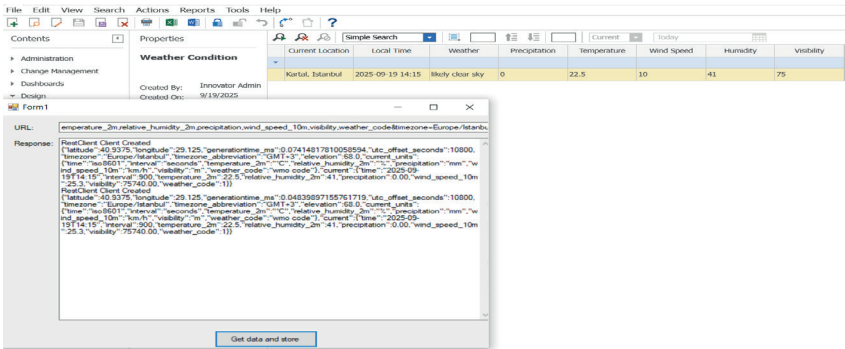


Figure 6. Weather conditions retrieved from Open-Meteo API and stored in Aras Innovator for mission validation.

Figure 6 illustrates this process: weather data such as temperature, wind speed, humidity, visibility, and precipitation are automatically retrieved via a REST service and stored in the PLM repository. By embedding weather data as mission-linked items, PLM ensures that each mission validation incorporates current and traceable environmental information.

For the freshwater monitoring scenario, the following thresholds are applied:

- Air temperature must remain within 0-40 °C.
- Wind speed must not exceed 10 m/s.
- Visibility must be at least 3 km.
- Relative humidity must not exceed 90%.
- Any precipitation automatically disqualifies the mission.

If any condition is violated, the PLM system records the violation and prevents the mission from being released. During execution, in-flight monitoring extends these checks, and violations trigger either warnings, operator decisions, or mission cancellation. The environmental validation rules used in this framework are summarized in Table 2, which lists the thresholds, severity levels, and associated PLM actions.

Table 2. Environmental constraints for UAV mission validation in PLM

Constraint	Threshold / Condition	Severity	Action in PLM
Temperature	$0\text{ }^{\circ}\text{C} \leq T \leq 40\text{ }^{\circ}\text{C}$	Hard cancel	Block mission release; auto-cancel in-flight if exceeded
Wind speed	$\leq 10\text{ m/s}$	Hard cancel	Prevent launch; return-to-home (RTB) if exceeded
Visibility	$\geq 3\text{ km}$	Hard cancel	Block mission approval; cancel if drops below threshold
Humidity	$\leq 90\%$	Warning	Operator notified; decision required
Precipitation	None (rain, snow, fog)	Hard cancel	Mission automatically canceled or rescheduled

3.4 Geographic and Regulatory Flight Constraints

Beyond environmental conditions, UAV operations must comply with geographic and regulatory restrictions defined by civil aviation authorities. These typically prohibit or limit UAV operations in sensitive areas such as air-

ports, hospitals, stadiums, military bases, protected ecosystems, and critical infrastructure.

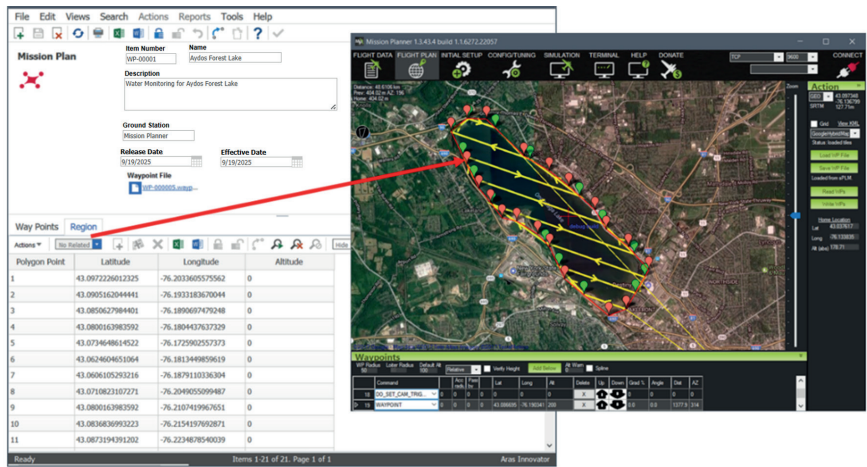


Figure 7. Mission plan management interface in Aras Innovator, showing mission definitions, restricted areas, and waypoint validation.

In the PLM framework, restricted areas are represented as RestrictedZone or No-Fly Area objects, modeled using polygon coordinates. During mission definition, the system automatically checks whether the mission’s designated region intersects with restricted areas. The mission planning interface, shown in Figure 7, provides a visual overlay of mission regions and restricted zones to assist operators in validating compliance before flight.

Table 3. Regulatory and geographic constraints for UAV mission validation in PLM

Constraint Type	Example Areas	Severity	Action in PLM
Airport proximity	Controlled airspace, approach paths	Hard cancel	Block mission approval; mission cannot be released
Sensitive sites	Military bases, hospitals, stadiums	Hard cancel	Prevent mission; require alternative region
Urban areas	Dense residential or commercial zones	Warning	Operator notified; must obtain waiver/approval
Protected zones	Ecosystems, cultural heritage sites	Hard cancel	Mission blocked; PLM enforces exclusion
Infrastructure	Energy facilities, communication hubs	Hard cancel	Mission blocked; automatic rerouting suggested

The validation rules applied to these restricted areas are summarized in Table 3, which outlines constraint types, severity levels, and the corresponding PLM actions. With mission requirements, environmental conditions, and regulatory constraints systematically modeled and validated in PLM, Section 4 describes how real-time mission execution data are integrated back into the system through a REST-based service architecture.

4. UAV Information Management System for Mission Management

4.1 REST-Based Architecture for UAV Mission Data Management

Mission execution in this framework requires a reliable mechanism to stream sensor observations from UAV platforms into the PLM environment while maintaining traceability to the mission, platform, and payload. To achieve this, a lightweight REST-based architecture was implemented, linking the UAV's onboard computer with Aras Innovator through a Python client, an ASP.NET service, and the Aras C# API. As illustrated in Figure 8, the architecture consists of three integrated layers:

- **REST Web Client (Python on Raspberry Pi):** The onboard computer collects environmental data, such as water pH, temperature, dissolved oxygen, and GPS coordinates. These readings are encapsulated in JSON messages and transmitted via standard HTTP methods (POST, GET, PUT, DELETE). The client also incorporates buffering and retries logic to handle intermittent connectivity.

- **REST Web Service (ASP.NET):** This service acts as a gateway, receiving data packets over an IP connection. Depending on the mission profile, several communication links can be employed. For short-range operations, Wi-Fi provides a straightforward solution with high bandwidth but limited coverage. For regional or beyond-line-of-sight missions, a cellular link (LTE/5G using a SIM card) offers wider coverage and stable throughput, enabling UAVs to transmit observations directly over the public internet. For remote or offshore operations where no terrestrial infrastructure exists, satellite communication provides global connectivity, albeit with higher latency and cost. The service validates schema and identifiers, applies authentication, and routes the requests to the PLM environment. In multi-UAV missions, reliable communication and real-time planning under multiple constraints are essential (Liu et al., 2025).

- **PLM Repository (Aras Innovator via C# API):** Once validated, the data is mapped to Aras Innovator using the Aras.IOM C# API. Each record is instantiated as a *WaterQuality* item and automatically linked to its corresponding Mission and UAV Platform items, ensuring full lifecycle traceability.

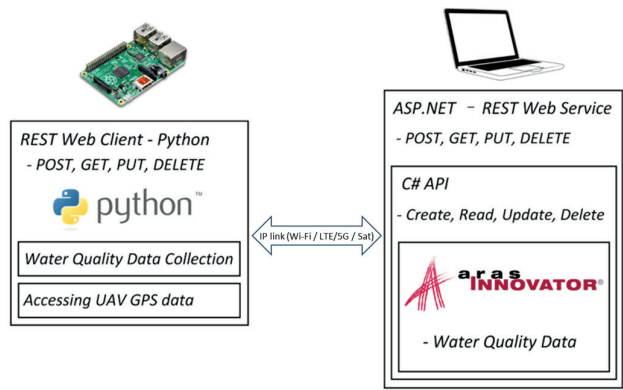


Figure 8. REST-based architecture linking UAV onboard systems with the PLM environment through a Python client, ASP.NET service, and Aras Innovator API.

The RESTful interface follows the standard request-response pattern: POST transmits new mission observations, GET retrieves stored records for visualization, PUT handles updates, and DELETE enables removals.

Table 4. Example fields included in UAV-to-PLM JSON payload

Field	Example Value	Description
mission_id	MSN-00051	Unique mission identifier
platform_id	UAV-0007	UAV configuration identifier
timestamp	2025-06-12T10:25:30Z	UTC timestamp of observation
lat, lon	40.95330, 29.23010	GPS coordinates of sampling point
pH	7.3	Water pH value
temperature_C	20.2	Water temperature (°C)
dissolved_oxygen_mgL	7.6	Dissolved oxygen concentration (mg/L)

Each UAV transmits its sensor readings in JSON format. The payload includes both measurement values and mission metadata, ensuring that every observation is traceable to a specific UAV configuration and mission plan. The key fields included in the UAV-to-PLM data transfer are summarized in Table 4.

Upon reception, the ASP.NET service validates the request and uses the Aras Innovator C# API to create a WaterQuality item. This item is automatically linked to its parent Mission and UAV Platform, ensuring that collected

data remains contextualized. To enhance reliability, the Python client implements local buffering and retry logic for cases of intermittent connectivity. Security is enforced through TLS encryption and token-based authentication in request headers. On the server side, validation rules reject incomplete or out-of-range data such as missing mission ID, invalid coordinates, or unrealistic sensor values, with all violations logged in PLM for audit.

A stateless, modular communication pipeline is maintained by this design. Operators can correlate mission data with UAV configurations, sensor specifications, and calibration history thanks to the verifiable digital record created by each transaction. The system guarantees compatibility with both PLM-side enterprise services and UAV-side Python applications by utilizing REST as the common protocol.

4.2 Mission Execution and Monitoring

The ground control station (GCS) and UAV platforms are used to carry out missions after they have been defined and verified in the PLM environment. Through the creation of a traceable digital record from planning to execution, the PLM system makes sure that every mission that is released has waypoints, constraints, and payload configurations associated with a particular UAV platform.

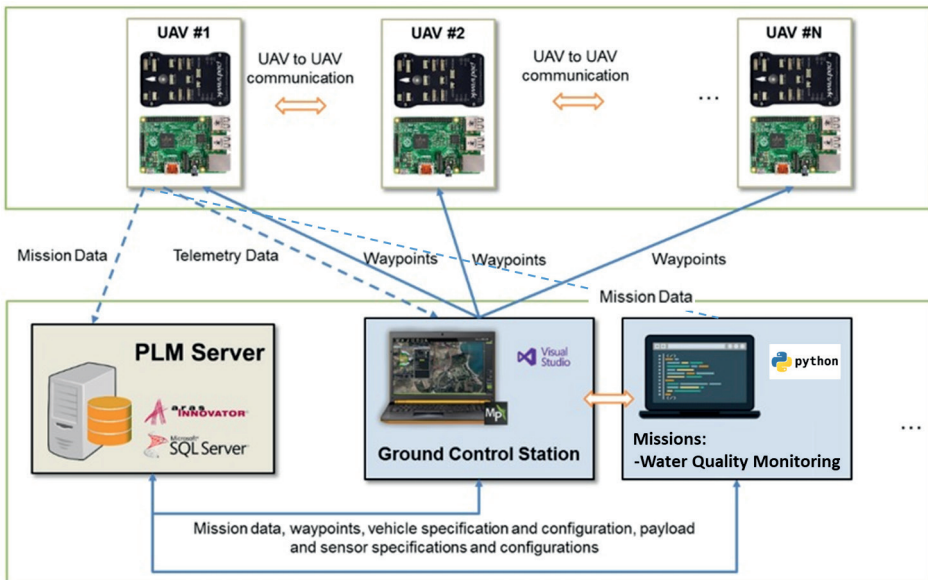


Figure 9. Mission execution workflow linking PLM-defined missions, the ground control station, and UAV platforms.

As illustrated in Figure 9, the execution process involves three main components:

- **PLM Mission Repository:** Missions are created and stored in Aras Innovator with associated metadata, including UAV platform configuration, payload definitions, and environmental or regulatory constraints. When a mission is released, its validated waypoints and parameters are transmitted to the GCS.
- **Ground Control Station (Mission Planner):** The GCS receives mission data from the PLM repository and translates it into commands that can be executed by the UAV. Operators can monitor progress in real time, with updates on UAV position, battery status, and payload state. The GCS also acts as an intermediary, forwarding mission updates, logs, or overrides back to the PLM environment.
- **UAV Platform and Payload:** During flight, the UAV executes the mission according to the transmitted waypoints and parameters. Payload sensors (e.g., water quality probes) collect data, which is streamed via the REST-based interface back to the PLM repository. Telemetry such as position, speed, and battery life is simultaneously monitored to ensure mission safety.

During execution, multiple categories of data are exchanged between the UAV, GCS, and PLM repository. These include mission plans, telemetry, sensor data, flight logs, and alerts. The key elements of this data exchange are summarized in Table 5.

This bidirectional workflow enables real-time monitoring and lifecycle traceability. Operators can verify that missions are being carried out as planned, while collected data is automatically linked to its originating mission and UAV platform. Any deviations, constraint violations, or environmental issues are logged in PLM, supporting post-mission analysis and potential re-use of mission templates in future operations.

Table 5. Example data exchanged during mission execution and monitoring

Data Type	Example Content	Source → Destination	Purpose
Mission Plan	Waypoints, altitudes, speed, payload settings	PLM Repository → GCS → UAV	Guides UAV execution according to validated plan
Telemetry	Position, velocity, battery, attitude	UAV → GCS → PLM	Real-time monitoring of UAV state
Sensor Data	pH, temperature, dissolved oxygen, images	UAV Payload → REST Service → PLM	Mission-specific observation data

Flight Logs	Dataflash logs, telemetry logs (tlogs)	UAV/GCS → PLM	Post-mission analysis and traceability
Alerts/ Violations	Low battery, no-fly zone breach, sensor fault	UAV/GCS → PLM	Ensures safety, compliance, and operator response

4.3 Post-Mission Data Integration and Traceability

After mission completion, all collected data and operational logs are consolidated within the PLM environment to ensure full lifecycle traceability. This stage links mission results not only to the executed flight plan but also to the UAV platform configuration, payload details, and subsystem calibration history.

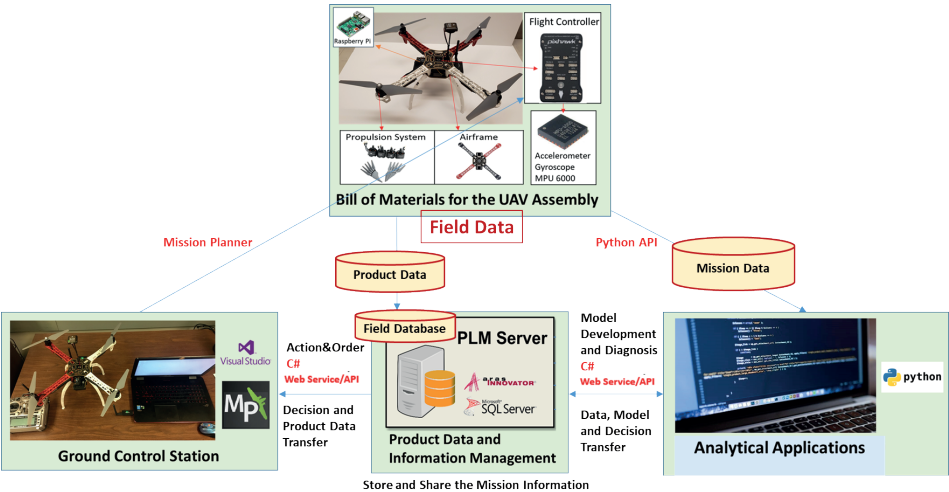


Figure 10. Post-mission data integration pipeline, linking UAV field data to product information and analytics in the PLM environment.

As illustrated in Figure 10, the post-mission workflow integrates three types of data streams:

- **Field Data:** Measurements collected during flight (e.g., water quality values, imagery, or telemetry logs) are stored as Observation items in PLM. These items are linked to the originating Mission, UAV Platform, and Payload, ensuring that each dataset is contextualized within its operational scenario.
- **Product Data:** Mission outcomes are connected to the UAV’s digital Bill of Materials (BOM), firmware version, and sensor calibration files. This

linkage ensures that performance assessments are always grounded in verified hardware and software states.

- **Mission Data:** Waypoints, mission plans, and external constraints such as weather conditions, no-fly zones are recorded and linked to each mission. This provides operational context and supports reuse in future deployments.

These data streams come together to create a digital thread that crosses planning, carrying out, and assessing. The primary data categories, their sources, and their functions within the PLM repository are compiled in Table 6.

Table 6. Categories of UAV data integrated into PLM after mission execution

Data Category	Example Content	Source	Purpose in PLM
Field Data	Sensor readings (pH, temperature, dissolved oxygen), UAV telemetry (battery status, GPS logs), flight logs	Onboard computer, payload sensors, flight controller	Evidence of mission performance; input for analysis and traceability
Product Data	UAV Bill of Materials (airframe, propulsion system, power unit), firmware version, calibration records	PLM repository (UAV configuration, CAD, specifications)	Links mission results to UAV configuration; supports lifecycle traceability and maintenance
Mission Data	Waypoints, mission plans, environmental conditions (weather API), restricted zone checks	Ground control station, PLM mission planner, external APIs	Provides operational context; enables mission reuse, compliance checks, and post-mission evaluation

Both knowledge reuse and operational traceability are supported by this integration pipeline. Operators can, for instance, copy an old mission template, change just the payload or waypoints, and then redeploy it with the assurance that previous configurations and results will still be available. Similar to this, anomalies found in post-mission analysis can be linked to particular calibration records or subsystems, offering important information for system improvement and maintenance.

The PLM environment ensures that UAV operations are carried out safely, assessed methodically, and improved iteratively through historical feedback by linking mission data with platform information and analytics. The next section builds on this foundation by demonstrating how missions are planned, executed, and monitored within the PLM-integrated environment.

5. Mission Planning, Execution, and Monitoring in PLM

5.1 Mission Workflow for Water Quality Monitoring

The previous sections introduced how UAV platforms are digitally represented in PLM, how mission requirements are modeled and validated, and how flight data is transmitted back into the repository through a REST-based architecture. Building on this foundation, this section demonstrates how the PLM environment is used to plan and track an actual freshwater quality monitoring mission, where a physical UAV and sensors are deployed and their properties are fully managed in Aras Innovator.

The mission begins with the selection of a UAV platform from the PLM repository. Unlike an abstract simulation, the repository contains actual UAV configurations used in practice, with their detailed specifications stored as Items. These include endurance limits derived from battery and propulsion characteristics, maximum payload capacity, firmware versions, and calibration records. When the UAV is selected for a mission, these parameters are automatically brought into the planning process, allowing PLM to assess feasibility and enforce constraints. For example, based on the UAV's stored performance data, the system can confirm how long the drone can fly under load and whether it can carry the intended sensors within safe limits.

The mission's payloads and sensors are then specified. This includes a set of physical probes that measure temperature, dissolved oxygen, and pH in the case of water quality monitoring. PLM contains the specifications, calibration history, and integration records for each of these sensors. PLM enables the tracking of the precise UAV and sensors deployed for a mission by connecting the payload items to the UAV platform. This guarantees reproducibility and accountability for repeated operations.

Mission Planner is then used to create the mission plan. The resulting plan is saved in PLM, and five waypoints are designated as sampling points throughout the survey area. Waypoint coordinates, sampling guidelines, and scheduling metadata are all included in this digital mission record and are connected to the chosen UAV and payloads. The plan can be obtained straight from PLM, modified as needed, and redeployed with version control if the mission is a rerun of an earlier operation, guaranteeing traceability throughout iterations.

Before execution, automated requirement checks are performed within PLM. Payload weight is compared against the UAV's maximum carrying capacity, endurance is checked against the estimated mission duration, and firmware/software compliance is verified. In addition, weather data is retrieved from an external provider and stored as a mission-linked item. These

environmental conditions including temperature, wind speed, humidity, and visibility are compared with operational thresholds defined in the PLM environment. Only if all validations are satisfied is the mission released for execution.

During mission execution, the UAV flies to the assigned waypoints and collects water samples using the onboard sensors. Measurements of pH, temperature, and dissolved oxygen are transmitted through the REST interface and stored in PLM as mission result items. Each measurement is automatically linked to its originating mission, UAV platform, and waypoint, preserving full context for later analysis.

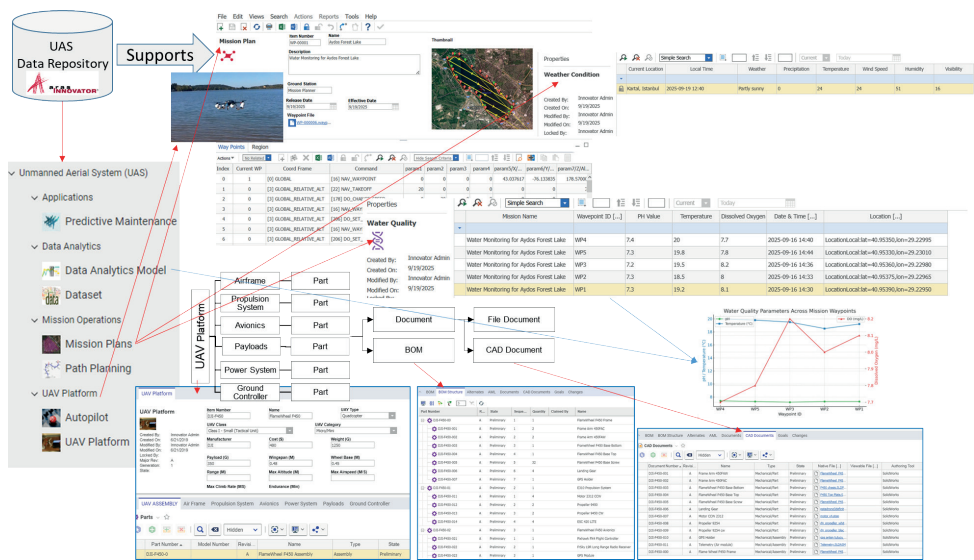


Figure 11. PLM-integrated workflow for UAV-based freshwater quality monitoring.

Finally, the collected mission data is evaluated within the PLM environment or exported to analytical applications. As shown in Figure 11, the PLM workspace consolidates UAV assemblies, mission requirements, waypoint definitions, and collected water quality results in one place. Data can be visualized across waypoints to identify spatial patterns, detect anomalies, or compare outcomes with previous missions. In this way, PLM not only supports safe and validated mission execution but also transforms operational data into a reusable digital asset that informs future planning.

5.2 Post-Mission Analysis and Traceability

As shown in Figure 11, the PLM-integrated workflow not only supports mission planning and execution but also enables comprehensive post-mission

analysis and traceability. Once the mission is completed and data is transmitted back to the PLM environment, all relevant information including UAV configuration, payload definitions, mission plan, environmental constraints, and collected water quality data is consolidated into a single digital record

Each observation, such as a dissolved oxygen reading at a waypoint, is stored in context with the UAV that carried the sensor, the calibration history of that sensor, the firmware version of the flight controller, and the validated mission plan. This linkage ensures that results are reproducible, anomalies can be explained, and compliance with operational requirements can be demonstrated.

The stored mission data also supports analytics and review. Water quality measurements can be visualized across waypoints to highlight spatial variations or compared against previous missions for trend analysis. By maintaining this data within PLM, operators gain the ability to perform multi-mission comparisons, support anomaly detection, or feed datasets into predictive models and machine learning applications.

PLM offers a version-controlled audit trail in addition to data analytics. To guarantee accountability and lifecycle visibility, every mission plan, result set, and validation check is recorded. Reusing pre-existing plans, adding new waypoints, or modifying missions for various payloads can all be done while keeping track of previous outcomes.

UAV missions become reusable knowledge assets by integrating post-mission analysis and traceability into the PLM workflow. This encourages long-term environmental monitoring, accountability, and ongoing improvement. Additionally, the PLM environment offers an integrated framework that allows for a smooth connection between mission execution and post-mission results. Consequently, UAV operations continue to be both scientifically sound and operationally successful.

6. Summary and Conclusions

Motivated by the need for reusable, traceable, and systematic approaches to UAV operations, this chapter introduced a framework for UAV mission planning and data integration based on Product Lifecycle Management (PLM). Although the use of UAVs for environmental monitoring, disaster response, and inspection tasks is growing, many mission management strategies currently in use lack lifecycle traceability and the ability to integrate collected data with operational constraints and UAV configurations. These issues can be resolved through data-driven feedback loops, governance, and digital representation by utilizing PLM.

A freshwater quality monitoring mission served as a demonstration of the framework's implementation on the Aras Innovator platform. The Item-Relationship-Item structure was used to model UAV platforms and sensors, allowing for automated checks on firmware compliance, payload capacity, and endurance. For traceability and reuse, mission plans with specified waypoints were made in Mission Planner and saved in PLM. Water quality measurements (pH, temperature, and dissolved oxygen) were streamed in real time from the UAV's onboard computer to Aras Innovator via a lightweight REST-based architecture. Complete contextual traceability was made possible by the automatic association of these records with their mission, UAV configuration, and environmental circumstances. In order to facilitate visualization, cross-mission comparison, and analytics model integration, PLM combined results with mission metadata after the mission.

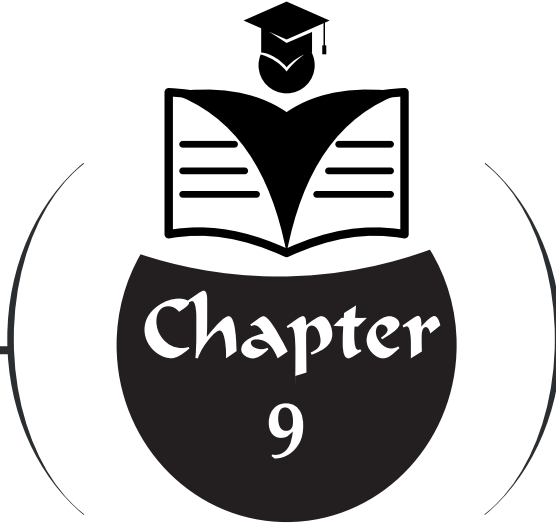
The following are the main advantages of this strategy:

- **Consistency and validation:** PLM makes sure that UAV endurance, payload, and environmental constraints are confirmed prior to flight by enforcing pre-flight checks.
- **Traceability and accountability:** Every mission is digitally connected to the precise UAV, sensors, and operating conditions, facilitating regulatory compliance and reproducibility.
- **Data integration and reuse:** By ingesting in-flight measurements as structured PLM items, future missions can benefit from systematic storage, visualization, and reuse.
- **Analytics readiness:** PLM facilitates trend analysis, anomaly detection, and integration with predictive models by maintaining mission data with context.

In conclusion, UAV missions become digital assets that are reusable, auditable, and analytics-ready when they are integrated into PLM. By connecting planning, execution, and post-mission analysis, this integration enhances operational efficacy, safety, and transparency. UAV applications in environmental monitoring will be greatly advanced by extending PLM-driven mission management with multi-UAV coordination and real-time decision support.

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SHORT PERSPECTIVE ON EXPLAINABLE ARTIFICIAL INTELLIGENCE IN HEALTH

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1. Towards Explainable AI

Artificial Intelligence (AI) is described as the automatic execution of processes by computers that mimic human thinking. AI techniques comprise approaches like machine learning, neural networks, and deep learning. With advancements in hardware, the popularity of deep learning has continued to grow. The foundations of deep learning were laid by Geoffrey Hinton, who developed deep neural networks with multiple hidden layers. Recent research indicates that deep learning can outperform traditional methods in certain problem domains (Rabia et al., 2024; Xu et al., 2021).

The internal reasoning of deep learning models is frequently non-transparent, leading them to be described as “black boxes.” Moreover, since deep neural networks contain hundreds of layers and thousands of parameters, understanding them becomes even more challenging.

Despite their complexity, deep learning models are preferred due to their superior performance. However, the need for transparency, interpretability, and explainability has arisen to make these models more understandable. To address this challenge concept of Explainable Artificial Intelligence (XAI) has emerged, aiming to help current and future practitioners better understand the internal workings of the model (Gunning, D., 2017). It can also serve as a guide for developers who seek to comprehend the model’s inner mechanisms.

A simple example of XAI in the healthcare domain is illustrated in Figure 1, focusing on diabetes risk assessment. Here, XAI is used to identify which features are important in the prediction process. For instance, the model evaluates features such as blood glucose level, insulin dosage, physical activity, dietary intake, and body mass index to predict diabetes risk. XAI provides a ranking of these features according to their importance in the prediction, with blood glucose level identified as the most influential factor.

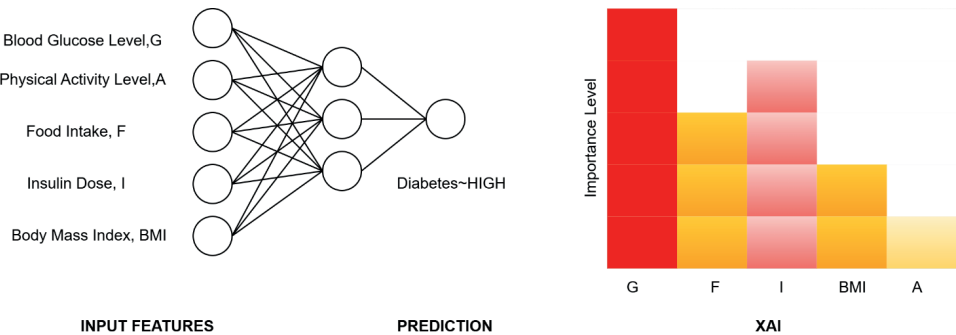


Figure 1. Example of XAI Applied to Diabetes Risk Prediction

By providing transparent explanations of decision-making processes, XAI addresses users' questions such as "Why was this output produced?", "Can I trust this model?", or "How can I correct errors?". This approach of XAI aims to enhance reliability while enabling users to better understand the model and correct mistakes, thereby supporting the development of innovative solutions. Its explainability feature captures the relationships between the outputs and the corresponding inputs (Das, A., & Rad, P., 2020; Machlev et al., 2022).

2. Methods and Principles of XAI

XAI aim to explain how model inputs are transformed into outputs. To achieve this, XAI algorithms are grounded in the principles of transparency, interpretability, and explainability (Wiki., 2025).

- Transparency relates to how clearly a model's internal learning and decision procedures can be observed and justified (Roscher et al., 2020).
- Interpretability represents the extent to which humans can grasp the logic behind the model's outputs (Murdoch et al., 2019; Lipton, Z. C., 2018).
- Explainability focuses on identifying the factors that most influence a model's predictions for given cases (Montavon, G., 2018).

Based on these principles, XAI methods commonly rely on examples, counterfactuals, latent semantics, rules, or feature/importance-based explanation mechanisms (Yeh et al., 2018; Wachter et al., 2017; Castro et al., 2002; Saarela, M., & Podgorelec, V., 2024; Hassija, V., 2024). Among these approaches, feature importance is the most widely used explanation method in classification models, as it clarifies the model's behavior according to the contribution of each feature (Saarela, M., & Podgorelec, V., 2024). In visual models, saliency maps or pixel attribution techniques are used to highlight important regions and visualize the model's decision process (Saarela, M., 2024).

In this context, the recommended XAI methods for domain experts and data scientists are summarized in Figure 2 (Viswan, V., 2024). These methods are primarily categorized along four dimensions: Scope, Applicability, Implementation, and Explanation Type. Each category is further subdivided into subcategories. Although this categorization functions as a classification, the categories are not mutually exclusive. The main goal is to facilitate users' understanding of XAI approaches.

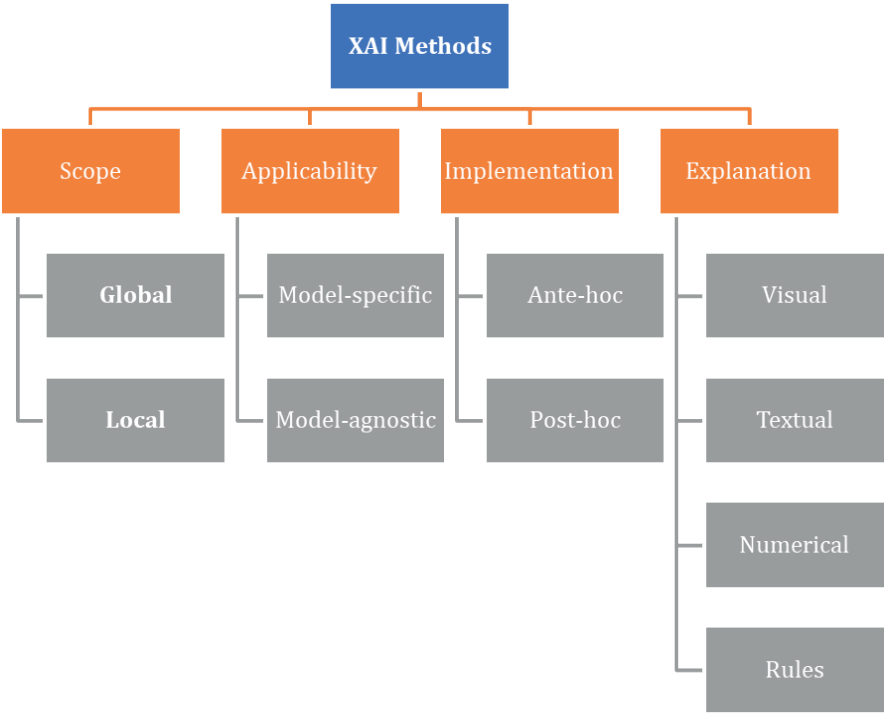


Figure 2. Classification of XAI Approaches

2.1 Scope-Based Methods

XAI approaches can be organized according to the level or scale at which they provide explanations. Global methods analyze the general patterns and functioning of a model, whereas local methods typically provide explanations focused on a single prediction or instance. Examples of global methods include attention mechanisms and capsule networks, which reveal how the entire model operates and identify the components most influential in the overall process. Local methods include techniques such as LIME and Grad-CAM (Viswan, V., 2024).

Local methods facilitate understanding of individual results and are preferred in error analysis and validation, whereas global methods are used to examine the systematic structure of a model and ensure reliable predictions (Viswan, V., 2024).

2.2 Applicability-Based Methods

This category refers to whether methods are specific to a particular model or can be applied broadly. Model-specific methods integrate explainability directly into the model and are usually optimized to understand its internal

dynamics. For instance, interpreting the weights and activation values of a neural network is model-specific.

Model-agnostic approaches offer explanations without depending on the internal structure of any specific model. Representative examples include LIME, LRP, SHAP, and Grad-CAM, which are typically applied post-hoc (Viswan, V., 2024). Model-specific techniques comprise decision trees, linear and logistic regression models, rule-based systems, and architectural explainability methods such as attention mechanisms and capsule networks. Due to their deep integration with a specific architecture, these methods cannot be directly transferred to other models (Viswan, V., 2024).

2.3 Implementation-Based Methods

XAI approaches can additionally be categorized according to their stage of implementation: ante-hoc and post-hoc. “Ante-hoc” (Latin: “before this”) refers to approaches directly integrated during model design and training. “Post-hoc” (“after this”) refers to methods applied after the model is trained, aiming to understand the behavior of an existing model.

Ante-hoc methods aim to ensure explainability from the beginning and include techniques such as decision trees, linear/logistic regression, and Bayesian models. These approaches are also called white-box or glass-box models and help users understand the decision-making process; they are especially preferred in applications requiring transparency (Viswan, V., 2024; Kumar, D., & Mehta, M. A., 2022).

Post-hoc methods provide an additional explanatory layer for black-box models. They analyze specific outputs retrospectively to identify which features influenced the result. In domains involving complex models, such as deep learning, post-hoc approaches enable interpretability without modifying the model’s internal structure. Representative post-hoc techniques, such as LIME and Grad-CAM, provide both local and global explanations, thereby enhancing interpretability (Viswan, V., 2024; Kumar, D., & Mehta, M. A., 2022).

2.4 Explanation-Level Methods

There are four commonly used types of explanations based on the model input: **numerical, visual, rule-based, and textual**.

- **Visual methods** visualize model decisions to highlight important regions (e.g., heatmaps). Grad-CAM is widely used in visual methods.
- **Textual methods** provide explanations in natural language but are generally limited to local applications due to high computational complexity.

- **Numerical methods**, including SHAP and Integrated Gradients, measure how individual input features influence the model’s predictions, making them particularly useful for detailed technical analysis.
- **Rule-based methods**, implemented with decision trees or rule-based models, present model decisions in a clear, rule-based format, which is particularly useful in scenarios requiring high interpretability (Kumar, D., & Mehta, M. A., 2022).

3. Overview of XAI Frameworks

Open-source and widely used XAI frameworks, developed to enable practical implementation of XAI approaches, are comparatively shown in Table 1.

Table 1. Comparative Summary of Widely Used XAI Frameworks

XAI Framework	Scope (Global / Local)	Applicability (Model-Specific / Model-Agnostic)	Implementation (Ante-hoc / Post- hoc)	Explanation (Visual / Textual / Numerical / Rules)	Programming Language
LIME (Ribeiro et al., 2016)	Local	Agnostic	Post-hoc	Visual, Textual	Python
SHAP (Lundberg, S. M., & Lee, S. I. (2017)	Both	Agnostic	Post-hoc	Numerical, Visual	Python
GRAD-CAM (Selvaraju et al.,2017)	Local	Specific	Post-hoc	Visual	Python
LRP (Bach et al., 2015)	Local	Agnostic	Post-hoc	Numerical	Python
InterpretML (Nori et al., 2019)	Global	Agnostic	Post-hoc	Visual, Textual	Python
Integrated Gradients (Sundararajan et al., 2017; Smilkov et al., 2017)	Global	Agnostic	Post-hoc	Visual, Numerical	Varies
Captum (Kokhlikyan et al., 2020)	Global	Agnostic	Ante-hoc	Visual, Textual	Python
DLIME (Zafar, M. R., & Khan, N., 2021)	Global	Specific	Post-hoc	Visual, Textual	Python
Anchors (Ribeiro et al., 2018)	Local	Agnostic	Post-hoc	Rules, Numerical	Python
DALEX (Biecek, P., 2018)	Local	Agnostic	Post-hoc	Visual, Numerical	Python
What-IF Tool (Wexler et al., 2019)	Local	Agnostic	Post-hoc	Visual, Numerical	Python / TensorFlow / JavaScript
Eli5 (Arya et al., 2021; Kawakura et al., 2022)	Local	Agnostic	Post-hoc	Visual, Textual	Python

XAI Framework	Scope (Global / Local)	Applicability (Model-Specific / Model-Agnostic)	Implementation (Ante-hoc / Post-hoc)	Explanation (Visual / Textual / Numerical / Rules)	Programming Language
EBM (Liu, G., & Sun, B., 2023)	Both	Specific	Post-hoc	Visual, Textual	Python
DeepLIFT (Miković et al., 2024; Zhang et al., 2020)	Global	Agnostic	Post-hoc	Visual, Textual	Python
TNTRules (Chakraborty et al., 2024)	Global	Agnostic	Post-hoc	Textual, Rules	Python

In Table 1, frameworks are classified based on different implementation types, scope, and explanation formats to enhance the interpretability of model decisions. According to the table, the predominant methods include LIME, SHAP, Grad-CAM, and LRP. These first four methods primarily focus on understanding deep learning-based models and visualizing which features are most influential.

3.1 Local Interpretable Model-Agnostic Explanations (LIME)

LIME is a technique designed to examine the impact of input data perturbations on a model’s predictions. It is a post-hoc approach, explaining the model after it has produced an output rather than relying on the model’s internal architecture. The method generates new samples by independently perturbing each input and drawing samples according to a normal distribution determined by the input feature’s mean and standard deviation (Ribeiro et al., 2016; Ali et al., 2023).

LIME essentially operates in four steps:

- Feature Extraction: Extracting meaningful features (e.g., segmentation).
- Sample Generation: Creating alternative samples around the target image by applying small modifications (e.g., adjusting brightness).
- Feature Attribution: Explaining the model at a local level (e.g., using a linear classifier).
- Explanation Presentation: Representing the importance of features using the model’s weights or activation maps.

Among XAI techniques, LIME is widely used; however, it faces certain challenges, such as limitations in data types and computational constraints. Various improvement approaches have been proposed to address these issues

(Utkin et al., 2020; Haunschmid et al., 2020; Laugel et al., 2018; Visani et al., 2020).

3.2 SHapley Additive exPlanations (SHAP)

SHAP enables explanations from local to global perspectives by fairly calculating the extent to which each feature influences the model's output. The approach originates from Lloyd Shapley's framework, which evaluates how individual players affect the collective outcome within a game. Accordingly, the Shapley value measures each feature's influence on a given model output.

SHAP extends LIME through the principles of cooperative game theory and has demonstrated greater consistency and robustness across model-specific explanations than comparable techniques. Unlike LIME, SHAP computes Shapley values for each features without the need to construct a local surrogate model (Roth, A. E., 1988; Kalasampath et al., 2025; Kumar et al., 2020).

3.3 Layer-wise Relevance Propagation (LRP)

LRP operates depending on the model's internal architecture, where it redistributes relevance from the output layer of a network back to the input layer (for instance, pixel values). LRP leverages the network architecture to compute relevance. The contribution of a neuron's output is attributed to the neurons that influence it through the activation function via backpropagation. This approach allows for an in-depth examination of the model's behavior and is effective in identifying potential errors in deep neural networks (Bach et al., 2015).

3.4 Gradient Weighted Class Activation Mapping (Grad-CAM)

Grad-CAM is a visualization approach that utilizes the gradient information flowing back into the convolutional layers to determine the importance of each neuron for a target class and generate a corresponding heatmap. Grad-CAM takes into account both the input image and the target class. Improving the transparency and interpretability of CNN-based models. It enables the interpretation of algorithms in visual tasks such as image recognition, object detection, and similar applications. The main goal is to emphasize the regions of the image that are most relevant to the target class (Selvaraju et al., 2017; Ali et al., 2023).

4. Applications in Health

XAI has attracted growing interest as it constitutes an important milestone in advancing AI methodologies. In the medical domain, it is crucial for models used in medical image interpretation, clinical decision support, and disease prediction to be explainable. Explainability brings transparency

to so-called “black-box” models by making visible the rationale behind their decisions and actions.

Applications of XAI in medicine can be examined along two main axes:

- Image-based,
- Text or database-based studies.

A summary of studies utilizing computer vision in medical XAI applications is presented in Table 2. In studies such as breast cancer prediction, COVID-19 diagnosis from chest X-ray images, skin cancer detect and classification, and brain tumor localization from MRI scans, model explainability approaches are commonly employed. In these types of studies, open-source and publicly accessible datasets are often used. For example, the ISIC (International Skin Imaging Collaboration) and HAM10000 datasets containing dermoscopic images are used for skin cancer; the NIH ChestX-ray14 dataset containing chest X-ray images is used for lung disease; COVID-CT datasets containing X-ray and CT images are used for COVID-19 diagnosis; Messidor and EyePACS datasets are used for retinal images; and the BreakHis dataset is used for breast cancer histopathology images. Computer vision effectively leverages XAI methods across these datasets in medical research.

Table 2. *Image-based XAI Applications Studies*

Application Area	XAI Method	Task / Objective	Reference
Skin cancer detection and classification	Grad-CAM, LIME	Identifying malignant skin lesions and visualizing key regions	(Raju et al., 2025; Vaghela et al., 2025; Mridha et al., 2023; Gupta, R. K., 2025; Hamim et al., 2024)
Breast cancer prediction	SHAP, LIME	Feature importance in diagnostic models	(Munshi et al., 2024; Maouche et al., 2023; Yagin et al., 2023)
Lung cancer recurrence prediction	LIME, SHAP, Grad-CAM	Localizing relevant regions in CT/X-ray scans	(Veeramani et al., 2025; Wani et al., 2024)
COVID-19 diagnosis via chest X-rays	SHAP, LRP, LIME, DeepLIFT, Grad-CAM	Highlighting infection regions in radiology images	(Aravinda et al., 2025; Rajpoot et al., 2024; Sarp et al., 2023)
Brain tumor localization	LIME, LRP, Integrated Gradients, Grad-CAM	Visual explanation of MRI-based predictions	(Agrawal, A., & Chaki, J. 2025; Saeed et al., 2024; Lamba et al., 2025)
Alzheimer's disease classification	LIME, SHAP, Grad-CAM	Brain MRI interpretability	(Zubair et al., 2025; Bootun et al., 2025; Mahim et al., 2024)

XAI approaches are also applied in text and database-based analytical tasks. Several studies related to such health applications are summarized in

Table 3. These include medical text classification, drug prediction, intensive care outcome prediction, and biosignal data analysis. Open-access datasets such as PubMed, MTSamples, UCI Machine Learning Repository, and PhysioNet Databases are commonly used for implementing XAI methods in text and database-based analyses.

Table 3. *Text and Data-based XAI Applications Studies*

Application Area	XAI Method	Task / Objective	Reference
ICU (Intensive Care Unit) patient outcome prediction	SHAP	Risk factor analysis for critical patients	(Guo et al., 2025; Yap et al., 2025; Moulaei et al., 2024)
Drug response prediction	LIME, LRP	Identifying key biochemical and genomic features	(Keyl et al., 2025; Xiang et al., 2025)
Medical text classification	LIME, SHAP	Interpreting clinical notes	(Zamir, M. T., 2025; Caterson et al., 2024)
Pain recognition from biosignals	LIME, SHAP	Feature attribution for physiological signals	(Sharma et al., 2024)
Nutritional geriatric decision support	SHAP	Model transparency in elderly care systems	(Santoso et al., 2025)
Cognitive health assessment	LIME, SHAP	Identifying relevant neurocognitive metrics	(Soladoye et al., 2025)

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