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# ARTIFICIAL INTELLIGENCE-BASED DECISION SUPPORT FOR PIPELINE INTEGRITY MANAGEMENT OF HIGH-PRESSURE NATURAL GAS TRANSMISSION SYSTEMS

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**Abstract:** This study presents an artificial intelligence-based decision support methodology for pipeline integrity management of high-pressure natural gas transmission systems. The proposed approach integrates technical documentation, pipeline characteristics and defect-pattern databases into a unified analytical framework to support the identification of potentially critical defect locations. A prototype database structure and AI-assisted search model were developed and evaluated in a representative test environment. The results indicate that the proposed methodology improves information retrieval, accelerates engineering assessment and supports more efficient integrity management while maintaining expert supervision. The developed framework demonstrates the practical potential of artificial intelligence for engineering decision support in pipeline operation.

***Keywords****: artificial intelligence, pipeline integrity, natural gas transmission, intelligent pigging, decision support, technical database*

## 1. INTRODUCTION

Natural gas transmission systems represent one of the most critical pieces of infrastructure supporting modern energy supply. Their safe and reliable operation depends on maintaining the structural integrity of thousands of kilometers of high-pressure steel pipelines, which function under constantly changing mechanical and environmental conditions (ISO 55000, 2014; ASME B31.8S, 2022). As these assets age, integrity management relies on accurate condition assessment, effective maintenance planning, and the rapid identification of potential defects.

Modern pipeline operators collect vast amounts of technical information throughout the lifecycle of their transmission lines. Design documentation, construction records, inspection reports, maintenance procedures, operational parameters, and data from in-line inspections (ILI) collectively form an ever-expanding engineering knowledge base. However, much of this information is scattered across a heterogeneous mix of digital and paper-based sources, making efficient retrieval and interpretation increasingly difficult (He et al., 2024). Consequently, experts often spend a significant amount of time searching for relevant documentation before any substantive technical evaluation can begin (API RP 1160, 2019; ISO 55001, 2024).

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Intelligent pipeline inspection has become the primary technology for assessing the condition of transmission pipelines. State-of-the-art inspection tools can detect corrosion, dents, cracks, weld anomalies, and various other types of defects with high positional accuracy (Gao et al., 2024). Although inspection technologies have evolved significantly over the past few decades, the interpretation of inspection results still requires a high level of engineering expertise and extensive comparison with historical documentation. Consequently, the growing volume of available data has shifted the primary challenge from data collection toward effective knowledge extraction and decision support (Khan et al., 2022).

Recent advances in artificial intelligence (AI), particularly in machine learning and large language models (LLMs), have created new opportunities to support engineering decision-making (He et al., 2024). AI systems have shown remarkable capabilities in processing large amounts of heterogeneous information, recognizing hidden correlations in complex data sets, and supporting experts' information retrieval. Rather than inducing engineering judgment, these technologies provide an opportunity to complement expert knowledge by rapidly analyzing documents that would otherwise require significant manual work to process.

Although AI is widely applied across numerous engineering fields, its use in the integrity management of transmission pipelines remains relatively limited (Chen et al., 2024; Li et al., 2024). Existing research focuses primarily on fault classification, predictive maintenance, or image-based inspection methods, while significantly less attention is paid to integrating engineering documentation and prior inspection knowledge into AI-assisted integrity assessment workflows (Gao et al., 2024; Yang et al., 2023). This shortcoming is particularly significant in long-life pipeline systems, where documentation accumulated over decades contains valuable information about failure formation, previous repairs, and recurring failure mechanisms.

This study proposes an AI-supported methodology to assist in the integrity management of high-pressure natural gas transmission pipelines, utilizing structured engineering databases and intelligent document analysis. The proposed framework integrates two complementary sources of information: a technical pipeline database describing the physical characteristics of individual pipeline sections, and a failure-pattern database containing engineering knowledge regarding typical failure mechanisms and assessment criteria. These databases are incorporated into an AI-supported search model capable of identifying potential links between pipeline characteristics and previously documented failures.

To evaluate the practical applicability of the proposed concept, a prototype database structure and a representative test environment were created using the engineering documentation from pipeline integrity management. The performance of the proposed methodology was evaluated by analyzing its ability to support fault identification, information retrieval and engineering decision-making.

The novelty of the work lies in the development of an integrated, AI-supported decision support method that combines structured engineering databases with natural language processing for the integrity management of supply lines. Instead of applying artificial intelligence directly to test signals, the proposed approach focuses on

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improving the utilization of engineering knowledge through intelligent processing of technical documentation. The methodology aims to complement existing integrity management practices by reducing the effort required for information retrieval while maintaining expert control over technical evaluation and maintenance decisions.

## 2. MATERIALS AND METHODS

### 2.1. High-pressure natural gas transmission system

The task of the high-pressure natural gas transmission system is to transport large quantities of natural gas safely and efficiently over long distances. The Hungarian transport network consists of nearly 6,000 km of high-pressure steel pipelines (PN 64 bar), which are connected by compressor stations, gas transfer stations, underground gas storage facilities and border crossing points. The network operates constantly changing pressure and flow conditions, while maintaining a high level of operational safety and security of supply (ASME B31.8S, 2022; FGSZ Ltd, 2024).

The long service life of transmission lines exposes the system to many degradation mechanisms. Among other things, external and internal corrosion, manufacturing defects, mechanical damage, stress corrosion cracking and fatigue-related failures. Consequently, maintaining pipeline integrity requires continuous monitoring, periodic inspection and risk-based maintenance planning. Modern integrity management therefore relies on the integration of operational data with test results and previous engineering documentation (API RP 1160, 2019; ISO 55000, 2014).

### 2.2. Intelligent pipeline inspection

Intelligent in-line inspection (ILI), commonly referred to as intelligent pigging, represents one of the most important non-destructive techniques for assessing the condition of transmission pipelines. Modern inspection tools can travel through operating pipelines while collecting high-resolution information regarding the internal geometry, wall thickness and structural condition of the pipe (API Std 1163, 2021; ASME B31.8S, 2022).



***Figure 1***
*Intelligent pipeline pig*

Depending on the objective of the inspection, various sensing technologies can be employed. Magnetic Flux Leakage (MFL) tools are primarily used to detect material loss defects caused by corrosion, while Ultrasonic Testing (UT) tools provide precise wall thickness measurements and crack detection. Geometric inspection tools

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can identify dents, ovality, and deformations, while inertial measurement units record the exact spatial location of any detected anomalies. Combining these technologies enables comprehensive integrity assessment without interrupting pipeline operations (API Std 1163, 2021; Crea et al., 2022).

Although high-precision inspection datasets are available from intelligent pipeline inspections, the associated engineering interpretation remains an essential part of the analysis. Individual anomalies must be evaluated in conjunction with pipeline characteristics, historical inspection records, construction documentation, and maintenance history before an appropriate engineering decision can be made. This interpretation process constitutes one of the most time-consuming stages of pipeline integrity management (API RP 1160, 2019; ASME B31.8S, 2022).

### 2.3. AI-supported database

The proposed methodology is based on integrating data into two complementary knowledge databases. The objective is to support AI-assisted decision-making in pipeline integrity management.

The first database contains the technical characteristics of pipeline sections. In addition to conventional parameters - such as diameter, wall thickness, steel grade, operating pressure, year of construction, and coating type - the database includes engineering parameters derived from the original technical documentation. These attributes provide a structured description of each pipeline section and establish the engineering context required for integrity assessment.

The second database contains descriptions of defect patterns compiled from engineering documentation, inspection reports, and integrity assessment procedures. Each defect record outlines the characteristic morphology, probable causes, critical engineering parameters, assessment criteria, and recommended maintenance measures. Rather than storing only numerical values, the database preserves descriptive engineering knowledge that can be processed using natural language models.

Separating pipeline characteristics from knowledge regarding defects enables flexible information retrieval, while ensuring that both datasets can evolve independently as new inspection results become available.

### 2.4. Artificial intelligence-based search model

The proposed search model employs a query-based workflow. In this approach, artificial intelligence analyzes multiple engineering documents simultaneously, rather than relying on a single inspection report (Lewis et al., 2020).

The process begins by extracting relevant technical information from the pipeline database. The AI system then compares these characteristics against descriptions of failure patterns stored in a knowledge base. It evaluates the matching engineering attributes - including material properties, operating conditions, inspection observations, and historical maintenance records - to identify which pipeline segments exhibit characteristics similar to previously documented failure incidents.

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Unlike traditional keyword-based document searches, the proposed methodology evaluates semantic relationships between engineering documents. Consequently, technically related information from various sources can be automatically linked, assisting engineers in evaluating faults and planning maintenance.

It is important to emphasize that the proposed methodology does not replace professional engineering judgment. Instead, artificial intelligence functions as an advanced decision-support tool. It accelerates document analysis, while ensuring that all technical decisions remain under expert supervision.

### 2.5. Implementation of the prototype

To evaluate the applicability of the proposed methodology, we developed a prototype using representative engineering documentation derived from pipeline integrity management.

The prototype consisted of a structured pipeline database, a knowledge base of defect patterns, and supplementary engineering documents describing inspection procedures and technical assessment criteria. The prototype utilized a large language model (LLM) combined with query-based information processing. This enabled the analysis of datasets through natural language queries and context-sensitive information retrieval.

The purpose of the prototype was to investigate whether AI-supported document analysis could improve the efficiency of information retrieval and facilitate the identification of locations where potentially critical defects might exist. Furthermore, it sought to determine whether it could support engineering decision-making during integrity assessments. The evaluation focused on the practical utility of the proposed workflow, rather than on automated defect classification. This also reinforces the intended role of artificial intelligence as a technology for supporting engineering decision-making (Lewis et al., 2020).

## 3. RESULTS

### 3.1. Development of an AI-supported pipeline database

The first result of the research was the creation of a structured engineering database designed to support the execution of integrity assessments using artificial intelligence. Instead of relying on isolated technical documents, the proposed solution integrates information from multiple engineering sources into a unified database. This data can be reliably processed by large language models (LLMs) (Lewis et al., 2020).

The developed database stores information regarding the pipeline at the level of individual pipeline segments. In addition to conventional technical parameters, the structure incorporates engineering data that is typically scattered across construction documentation, inspection reports, and maintenance records. This approach enables the AI system to evaluate technical information within its engineering context, rather than merely analyzing isolated parameters.

The three primary objectives of the database architecture are designed as follows:

- integration of heterogeneous engineering documentation;

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- a standardized representation of pipeline characteristics;
- efficiently retrieve information relevant to integrity assessments.

A total of four categories of engineering information have been incorporated into the proposed database:

- geometric features,
- material properties,
- operating parameters,
- previous integrity information.

The implemented structure allows for the simultaneous storage of both numerical and descriptive engineering data. Consequently, parameters such as pipeline diameter, wall thickness, and operating pressure can be analyzed in conjunction with textual descriptions extracted from inspection reports or maintenance documentation. This integrated structure facilitates the combined analysis of numerical and descriptive engineering information. Furthermore, it provides a more comprehensive overview of pipeline integrity data compared to traditional spreadsheet-based documentation.

The engineering attributes in the database were selected based on their relevance in the assessment of pipeline integrity and the formation of defects. Susceptibility to corrosion, mechanical stresses and parameters influencing previous maintenance activities were given special attention.

***Table 1***

*Main categories of the developed pipeline database*

| Data category | Typical parameters | Engineering relevance |
|---|---|---|
| Pipeline geometry | diameter, wall thickness, length | structural behavior |
| Material properties | steel grade, manufacturing process, coating | failure resistance |
| Operational data | operating pressure, temperature, commissioning year | loading conditions |
| Integrity history | ILI reports, repairs, excavations, previous defects | risk assessment |

Compared to traditional engineering documentation, the proposed database significantly reduces the effort required to identify pipeline sections with the same technical characteristics. Instead of manually reviewing multiple documents, engineers can retrieve all the information with a single structured query. This integrated data structure also provides the necessary basis for subsequent AI-based semantic analysis.

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### 3.2. Development of the error pattern knowledge database

The second major result of the research was the creation of a structured knowledge database of defect patterns. Unlike traditional defect catalogs, which primarily store observations from inspections, the proposed database was designed to preserve engineering knowledge describing the characteristics, probable causes, and evaluation criteria for each type of defect. The knowledge base was constructed using engineering documentation related to pipeline integrity management, interpretation procedures for intelligent pipeline inspections, and defect assessment practices developed for high-pressure transmission pipelines (API RP 1160, 2019; ASME B31.8S, 2022).

Instead of evaluating inspection results as isolated observations, the proposed methodology identifies semantic and engineering relationships between technically similar defects. Consequently, defects with comparable geometric characteristics, degradation mechanisms, or operational histories can be analyzed collectively by the AI model (He et al., 2024).

The structure has been categorized into the following five main groups of information:

- defect identification,
- characteristic geometry,
- degradation mechanism,
- engineering assessment criteria,
- recommended maintenance measures.

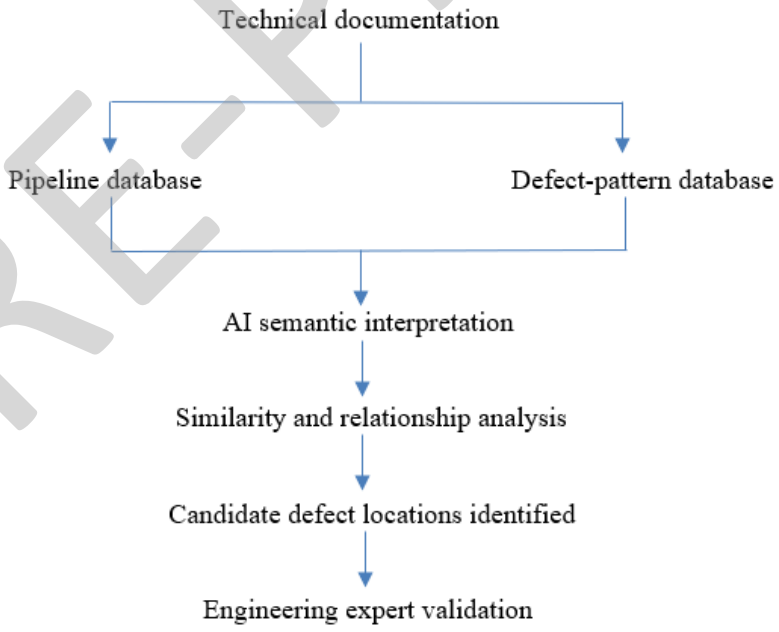



***Figure 2***
*Workflow of the proposed AI-supported knowledge framework*

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The proposed architecture enhances traditional integrity management approaches by integrating structured engineering data and descriptive technical knowledge into a unified, AI-supported framework. Rather than analyzing solely numerical parameters, the AI model evaluates the semantic relationship between pipeline characteristics and historical defect descriptions.

Another advantage of the developed database is its scalability. New inspection reports, excavation findings, and maintenance records can be incorporated without requiring modifications to the overall database architecture. Consequently, the available engineering knowledge expands continuously throughout the entire operational lifespan of the transmission system.

The integration of the pipeline database and the defect pattern database constitutes the core innovation of the proposed methodology. Together, these databases provide the information environment necessary for AI-supported defect identification.

### 3.3. Prototyping and AI-assisted fault identification

After the development of the pipeline database and the fault sample knowledge base, a prototype decision support system was created to evaluate the applicability of the proposed methodology under representative engineering conditions.

The prototype reproduces the typical workflow of an integrity engineer when evaluating the results of an intelligent pipe test (ILI). Instead of analyzing the test reports separately, the AI model simultaneously processed technical documentation, pipeline characteristics, and previous integrity information to identify engineering relationships between multiple data sources.

The evaluation process consisted of five successive stages:

- retrieval of the technical characteristics of the pipeline;
- retrieval of previous investigation records;
- semantic comparison with the error pattern database;
- prioritization of technically similar fault cases;
- engineering validation of the generated recommendations.

In contrast to traditional document retrieval systems based on keyword matching, the proposed workflow was used to interpret engineering terminology. As a result, similar technical descriptions from different documents could be linked even if they did not use the same terminology. This capability proved particularly valuable in the case of historical documentation produced by different engineering groups over several decades.

The AI model was not intended to replace engineering error assessment. It produced a prioritized list of technically relevant pipeline sections to support peer review and maintenance planning. This design philosophy was intentionally chosen to ensure that final integrity decisions remain the responsibility of trained engineers, while significantly reducing the time required for information retrieval.

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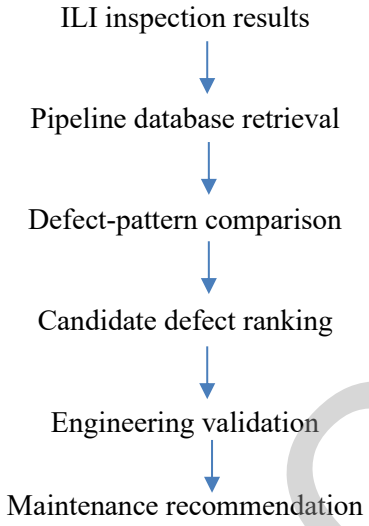



***Figure 3***
*Workflow of the prototype AI-assisted integrity assessment*

## 4. PRACTICAL APPLICABILITY OF THE MODEL

### 4.1. Purpose of the practical test

To assess the practical applicability of the AI-based wire integrity debugging concept, the previously presented theoretical approach was also examined in a test environment. The aim was to check whether the relationships relevant to wire integrity can be identified by the structured processing of technical data from different sources, the systematization of typical failure patterns, and the use of artificial intelligence. The significance of the practical test was given by the fact that the theoretical model alone does not yet prove the actual usability. To do this, it was necessary to create a test dataset, perform the analysis process, check the results, and examine how consistent the re-application of the same search criteria provides results.

Therefore, during the testing, it was not only evaluated whether artificial intelligence is able to recognize technically meaningful relationships. It was also an important aspect how accurate, verifiable and repeatable the results obtained were. These properties are of fundamental importance in the case of a technical support system, the results of which can later influence the assessment of the condition of the pipeline and the planning of further tests.

### 4.2. Design of the test model and control

For the practical test, a test pipeline database was compiled based on an intelligent ferret report. The report contained the technical characteristics recorded along the examined pipeline section in MS Excel format. Such data provided a suitable starting point, as they allowed for an overview and comparison of the various parameters in

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a structured form related to the pipeline route. Another defining element of the test model was the failure schema database. In it, technical correlations and patterns were systematized that can help in recognizing conditions related to possible failures. The aim of the joint application of the two databases was to enable artificial intelligence not to interpret isolated data, but to be able to examine the possible relationships between the characteristics of the pipeline and the failure patterns.

The interpretation was supported by further documents. This included documentation describing the meaning of the individual columns of the pipeline database, the content of the technical parameters and the relationships relevant to the searches. The aim of this was to ensure that the analysis was not based solely on keywords or simple numerical matches, but that the content of the technical data could also be interpreted.

As an important element of the test, a control table with formulas was also created. This made it possible to search the spreadsheet based on certain relationships recorded in the error schema database. Thus, the results of artificial intelligence could be compared with the results of a rule-based, formula-based control solution.

The control table provided a reference for checking the AI hits. With its help, it was possible to examine not only whether artificial intelligence provided an answer to the question asked, but also to what extent the patterns found matched the correlations that could be searched based on the defined rules.

### 4.3. The process of running the test and fine-tuning

In the created test environment, searches were carried out using ChatGPT Pro and Microsoft Copilot. The primary goal of the study was not to rank the performance of the two AI tools, but to determine whether the developed databases, documents and search logic provide a suitable basis for consistently exploring technical connections.

During the test, different strengths were observed for the two devices. In my experience, Copilot handled uploaded DOCX and XLSX documents more efficiently, especially in interpreting their structure and formatting, as well as extracting technical data. ChatGPT Pro showed more favorable experiences in recognizing correlations, performing search tasks, and processing textual content. These observations reflect the experience gained in the specific test environment and cannot be considered a general performance comparison between the two devices.

During testing, the search instructions and documentation were specified several times. When formulating the tasks, the AI task was to indicate if any information or instructions were unclear.

During the study, I also tried to improve the results by reducing the amount of information to be processed at the same time. During the study, to reduce the amount of data to be processed at the same time, the main aspect was not always to search for all error schemas at the same time, but to break down the analysis into smaller parts. This approach helped to separate the individual subtasks and gave them the opportunity to check the results step by step.

Before the testing began, a success criterion was defined. The method is considered successful if the same complete and accurate results are obtained at least nine

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times out of ten consecutive searches. This means an effective result of at least 90%. The threshold set required not only the existence of relevant results, but also their consistent and repeatable production.

### 4.4. Results obtained during the study

Based on the practical test, the developed method was able to support the exploration of correlations and repetitive patterns relevant to wire integrity. The structured design of the wire database and the fault schema database allowed for the uniform management of technical information from different sources. This provided a good starting point for artificial intelligence to look for relationships between line parameters and pre-recorded failure patterns.

During the runs, it was possible to identify repetitive patterns that can be associated with the development of certain failures. This experience confirms that the data structure and search approaches created may be suitable to support the preliminary examination of potentially relevant pipeline sections. Therefore, the practical test did not remain exclusively on a theoretical level: the concept was tested through searches and verification of actual data sets.

However, there was a significant limitation in terms of effectiveness. The target of 90% was not achieved during testing. At the end of the attempts, the search accuracy varied between 60% and 90%. In addition, there were significant differences between the results of consecutive searches on the same data set; experience shows that in some cases these were as high as 60-70%.

This indicated that artificial intelligence was able to recognize relevant correlations, but the results were not always sufficiently stable and reproducible. Therefore, in addition to producing the right match, the consistency of the search process also proved to be an area of the model that needed further development.

## 5. Conclusions

The increasing complexity of pipeline integrity management requires engineering methods that can process the ever-expanding amount of technical information. While intelligent pipe inspection technologies provide high-precision status data, the interpretation of test results remains highly dependent on the experience of integrity engineers and the availability of historical documentation. The present study demonstrates that artificial intelligence can effectively complement traditional integrity assessment by improving the organization and retrieval of engineering knowledge (ASME B31.8S, 2022; API RP 1160, 2019; He et al., 2024).

The developed database architecture provides a structured framework for combining these heterogeneous sources of information into a unified knowledge environment. The separation of pipeline characteristics and error pattern descriptions has proven to be advantageous as it allows both datasets to be expanded independently while maintaining their semantic relationships. This modular organization also facilitates long-term maintenance of the knowledge base after the completion of new investigation campaigns.

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The prototype implementation demonstrated that semantic document retrieval offers significant advantages over traditional keyword-based searches. Engineering documents produced by different organizations or during different operating periods often use inconsistent terminology to describe similar degradation mechanisms. Traditional document management systems often fail to recognize these relationships because they rely on precise keyword matching. In contrast, the proposed AI-assisted workflow evaluates contextual similarities between engineering descriptions, allowing for the retrieval of technically related information despite terminological differences.

However, the proposed methodology has several limitations. First, the quality of AI-generated recommendations directly depends on the completeness and consistency of the available engineering documentation. Missing test reports, incomplete maintenance records, or inconsistently formatted technical documents can reduce retrieval performance. Second, the prototype was evaluated using representative engineering datasets, rather than a complete operational database of a transport system operator. Consequently, further validation of larger datasets would further increase confidence in the generalizability of the proposed approach.

Another important limitation relates to the role of AI in engineering decision-making. While large language models can efficiently analyze extensive technical documentation, they cannot replace engineering expertise or professional responsibility. The proposed methodology should therefore be understood only as a decision support tool for certified integrity engineers. Final assessments of failure severity, repair priority and operational safety should remain under expert supervision in accordance with relevant engineering standards and legal requirements (ISO 55000, 2014; ASME B31.8S, 2022).

Future research should focus on augmenting the database architecture with quantitative risk assessment models, geographic information system (GIS) integration, and real-time operational data from supervisory management and data collection (SCADA) systems. Combining these sources of information with artificial intelligence can provide a comprehensive digital framework that supports predictive integrity management throughout the operational lifecycle of transmission pipeline systems.

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