PREDICTIVE MODELING OF HYDROGEN-INDUCED CRACKING (HIC) IN X80 GRADE PIPELINE STEELS USING MACHINE LEARNING INTEGRATED WITH METALLURGICAL PARAMETERS

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Abstract
Hydrogen-induced cracking (HIC) is a critical integrity threat in API X80 pipeline steels operating in sour environments because it initiates internally at hydrogen trap sites and progresses through stepwise crack linking. With increasing sour-service exposure and the emerging transition toward hydrogen-blended transport systems, there is a growing need for predictive tools that can estimate HIC susceptibility before failure occurs. This study develops an interpretable machine learning framework for predicting HIC behavior in X80 steels by integrating sour-environment variables with metallurgical parameters that control hydrogen uptake, trapping, and crack propagation. The dataset combines key descriptors of metallurgical heterogeneity (segregation index, banding index, MA fraction), inclusion population (density and maximum inclusion size), localized hardness (maximum HV), and environmental severity (pH and H_2S partial pressure). HIC response is quantified using standard indices (CLR, CTR, CSR) and a susceptibility classification scheme. Results show that HIC response is strongly nonlinear, and ensemble machine learning models outperform baseline approaches for predicting CLR and classifying susceptibility. Metallurgical pattern analysis confirms that HIC severity increases with inclusion density and inclusion size, segregation and banding intensity, MA fraction, and hardness peaks, particularly under higher H_2S partial pressure and lower pH. Explainability analysis ranks sour severity, segregation-banding structure, inclusion metrics, and hardness localization as the most influential predictors, reflecting the mechanistic pathway of hydrogen entry, trapping, crack initiation, and crack linking. The framework provides a practical basis for steel quality assurance and risk-based inspection planning by enabling early prediction of HIC risk in X80 pipeline infrastructure under sour and hydrogen-transition service conditions.

1. INTRODUCTION

1.1 Background: X80 pipeline steels and integrity challenges

X80 grade high strength low alloy (HSLA) line pipe steels are extensively used in long distance oil and gas transmission systems because they offer high strength, reasonable toughness and good weldability with the reduction of wall thickness and improved economic performance. Produced mostly by thermo-mechanical controlled processing (TMCP), X80 steels have obtained refined microstructure suitable for large-diameter pipeline working under high internal pressures. Despite their pervasive deployment, problems of integrity are on the rise because of the evolving operation environments and the role of pipeline infrastructures in the global transition in the energy sector (Wu et al., 2024; Lv et al., 2025).

One important integrity issue is hydrogen related degradation. In conventional service, pipelines can be used in a sour environment where hydrogen sulfide encourages hydrogen entry to steel. Hydrogen-induced cracking (HIC) in such cases becomes important as it is able to initiate internally by accumulation of hydrogen at microstructural traps and inclusions, even in the absence of external applied stress. The susceptibility of X80 steel to HIC is strongly metallurgically controlled by such features as inclusion characteristics, segregation, banding, microstructure morphology, and local hardness variations, which can vary from heat to heat and processing condition to processing condition (Wu et al., 2024; Lv et al., 2025).

At the same time, the energy systems are moving towards lower-carbon transport networks. Hydrogen blending into existing natural gas pipelines and increasing the CO2 pipeline infrastructure of transport are increasingly becoming an option as part of decarbonization. These transitions bring forward some new material risks, especially since exposure to hydrogen increases the susceptibility to cracking and makes conventional approaches to managing the integrity of these materials much more difficult. Therefore, there is a growing need for predictive integrity frameworks that can help in evaluating cracking susceptibility based on both the combination information of metallurgical parameters and service conditions rather than referring to only a periodical inspection condition or simplified acceptance criteria. Such predictive approaches are consistent with clean hydrogen development priorities and emerging hydrogen infrastructure planning (Li et al., 2021).
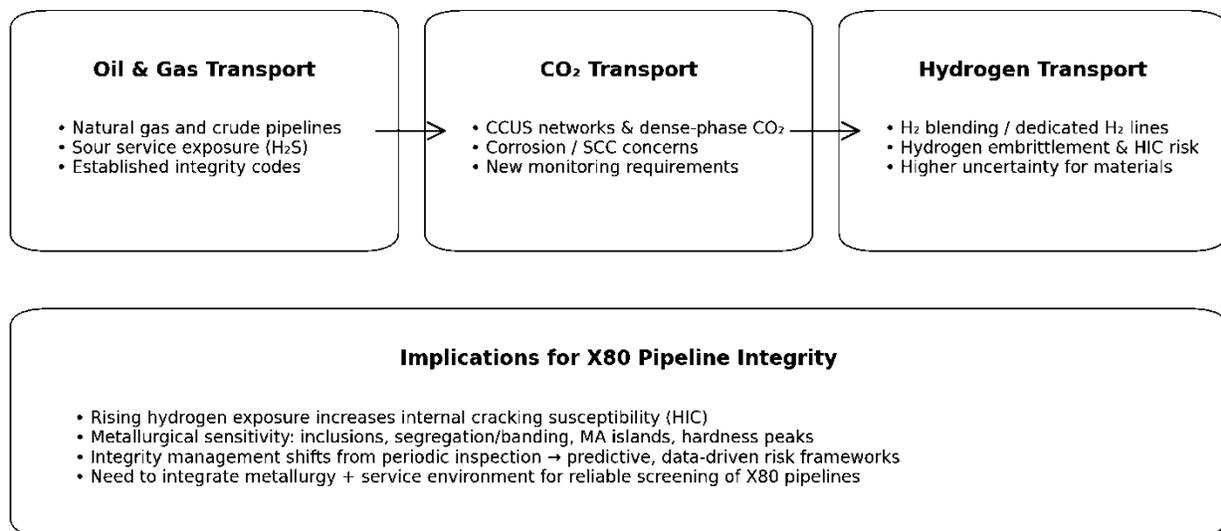

Figure 1: Energy transport transition framework (Oil and Gas $\rightarrow$ CO_2 $\rightarrow$ H_2) and its implications for X80 pipeline integrity.

1.2 Hydrogen-induced cracking (HIC) in pipeline steels

Hydrogen-induced cracking (HIC) is a form of internal cracking in steels that occurs when atomic hydrogen penetrates the metal lattice and accumulates at vulnerable internal sites, leading to crack initiation and growth. Unlike surface corrosion damage, HIC is typically characterized by the formation of cracks within the steel matrix, often parallel to the rolling direction, and frequently concentrated in mid-thickness regions where inclusions and segregation bands are more prevalent. A defining feature of HIC is that it can occur without externally applied tensile stress, making it particularly dangerous for pipelines because damage may develop silently and progress before being detected through inspection (Wu et al., 2024; Pourazizi, 2020).

HIC is closely related to other hydrogen-assisted cracking mechanism but is unique in its driving conditions as well as the morphology of the cracks. Sulfide stress cracking (SSC) usually requires the presence of a tensile stress (applied or residual) associated with the uptake of hydrogen in the case of sour environments, and normally takes the form of brittle cracking, often in areas of high hardness, as at welds or heat-affected zones. Stress corrosion cracking (SCC), on the other hand, is affected by a certain corrosive environment, stress state and electrochemical processes, resulting in branched surface cracks that grow under a sustained stress condition. In contrast, HIC is predominantly under the control of hydrogen diffusion and trapping in the steel and internal cracks form even in an absence of significant external loading. Therefore, in contrast to SSC and SCC that are stress-driven cracking mechanisms, HIC is a fundamentally hydrogen accumulation driven internal fracture phenomenon (Lv et al., 2025; Wu et al., 2024).

The severity of HIC in the case of pipeline steels becomes quite apparent in sour service environments with a presence of hydrogen sulfide (H_2S). In wet H_2S environment, the electrochemical reactions on the surface of the steel create the atomic hydrogen. Normally, much of this hydrogen recombines to form molecular hydrogen gas and escapes; but the source of great concern is the fact that H_2S is a recombination poison preventing the recombination of hydrogen atoms in an efficient way. As a result, more atomic hydrogen enters the steel, more hydrogen enters the metal. After absorption, hydrogen (or in short, H_2) will diffuse through the microstructure and be trapped at microstructural discontinuities (excluding fracture) such as inclusions (particularly as MnS and complex oxide inclusions in), grain boundaries and the segregated banding zone. These traps lead to local enrichment of hydrogen, leading to local increase in internal pressure and decrease in cohesive strength and the initiation of crack nucleation (Pourazizi, 2020; Lv et al., 2025). Crack propagation of HIC is very much dependent on the metallurgical structure of linepipe steels. After the initiation of the cracks at the hydrogen-rich traps, cracks grow along the weak interface and may connect with adjacent cracks via crack step-by-step coalescence. This process of connecting cracks is an important reason why HIC may advance from microscopic cracking to long crack networks where the pipeline integrity is compromised. Since steels such as X80 often exhibit microstructural variations in the thickness and rolling directions, the interaction of the diffusive pathway through which hydrogen acts, the distribution of inclusions and the severity of their segregation is central in the overall HIC susceptibility. Consequently, HIC resistance not only needs to control the service environment appropriately but also needs to be cautious when designing and processing the steel in order to minimize the presence of hydrogen traps and microstructural heterogeneity (Wu et al., 2024; Pourazizi, 2020).
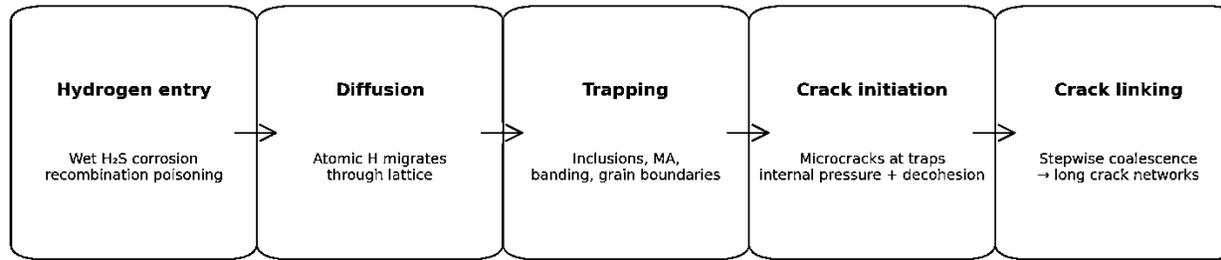
Hydrogen entry → diffusion → trapping → crack initiation → crack linking

Figure 2: Schematic mechanism of HIC: Hydrogen entry → diffusion → trapping → crack initiation → crack linking.

1.3 Metallurgical origin of HIC susceptibility in X80

Hydrogen-induced cracking (HIC) for X80 pipeline steels is essentially controlled by metallurgical heterogeneity, since the internal structure of X80 steels affects the locations of hydrogen accumulation and its ease of diffusion along with the location and connectivity of cracks. Despite the fact that X80 is a design of a high-performance HSLA steel, variations of inclusion population, intensity of segregation, phase distribution in microstructure and hardness gradient can alter HIC resistance considerably. In practice, HIC is hardly controlled by a single factor, its occurrence is rather the result of the mixed effect of hydrogen traps and the path of crack propagation being favored embedded in the steel matrix (Wu et al, 2024; Pourazizi, 2020).

One of the main metallurgical factors is the presence and its morphology of non-metallic inclusions. In pipeline steels, some of these inclusions like manganese sulfide (MnS), alumina (Al2O3), silicates and complex oxysulfide can function as strong hydrogen trap sites. MnS inclusions in particular are extensively associated with HIC due to the elongate morphology (morphology along one direction (rolling direction)). Such inclusions produce the interfacial discontinuities between the inclusion and matrix where hydrogen is accumulated and produce local stress concentration and decohesion. Larger inclusions and higher inclusion density increase the probability of crack nucleation whereas elongated inclusions result in crack alignment and ease of crack coalescence. Oxide inclusions & complex inclusions can also lead by the creation of micro voids, weak interfaces or local electrochemical heterogeneity leading to the localization of hydrogen in accelerated way (Pourazizi, 2020; Wu et al., 2024).

Banding and centerline segregation are another major metallurgical cause of HIC susceptibility especially in TMCP plates. During the solidification and hot rolling processes, alloying elements and impurities can settle towards the centerline and form bands with a non-uniform composition with some zones becoming compositionally enriched. These regions tend to have modified microstructure, increase in hardness and increase in the density of inclusions. As a result of this hydrogen has a tendency to pile up in banded areas of segregation and the cracks propagate in these planes of weakness more easily. Crack linking is more severe where multiple microcracks take the lead in within segregated bands and then link together to form a stepwise cracking networks. Therefore, the banding index and the segregation intensity are often employed as metallurgical tools for evaluating the HIC risk in line pipe steels (Wu et al., 2024; Pourazizi, 2020; Natarajan, 2018).

Microstructure phase distribution is also very important. X80 steels often contain a mixture of acicular ferrite, bainite and other proportions of

polygonal ferrite based on processing conditions. While refined ferritic structures typically improve toughness and crack-sensitivity, bainite regions and martensite-austenite (MA) constituents can have a detrimental effect on hydrogen assisted cracking. MA islands are especially detrimental because they act as hard brittle microstructural zones that have strong hydrogen trapping capability. Hydrogen concentration around or in MA regions leads to local decrease of ductility and tendency of brittle crack initiation. Similarly, microstructural heterogeneity, where hard phases are clustered within softer ferritic zones, creates local stress gradients that favor crack nucleation and accelerate propagation. Therefore, the volume fraction and distribution of MA constituents, as well as the bainite-to-ferrite ratio, are important metallurgical parameters for predicting HIC susceptibility in X80 steel (Oh et al., 2024; Pourazizi, 2020).

Hardness gradients further influence crack propagation and crack stability. Although HIC can initiate without external loading, crack growth and linking are facilitated when the steel contains localized high hardness zones. Such hardness gradients frequently occur across the plate thickness due to microstructural variation, segregation bands, or in the vicinity of weld heat-affected zones. Higher levels of hardness lower the resistance to hydrogen assisted brittle fracture, making the initiated crack more likely to propagate. On the other hand, more homogeneous hardness distribution and refined low-hardness microstructures are mainly associated with better resistance of steels to HIC growth and crack coalescence. Therefore, hardness mapping and hardness statistical indicators (maximum hardness, hardness variance and hardness gradient index) are of interest as predictive features at the integration of metallurgical parameters into machine learning models of HIC susceptibility (Oh et al., 2024; Wu et al., 2024).

To sum up free inclusion is a site of initiation; segregation and banding are rehabilitation paths of preferred Arren propagation; microstructure phases are the control point of hydrogen and brittleness; and gradients of hardness determine the degree of crack growth. These metallurgical features can explain the aggregate effect that steels with similar chemical composition may still have a major difference in HIC performance. Hence, any predictive modeling protocol for X80 must include metallurgical descriptors to give the proper physical origin of the cracking susceptibility (Wu et al., 2024; Pourazizi, 2020; Natarajan, 2018; Oh et al., 2024).

Table 1: Metallurgical factors controlling HIC susceptibility in X80

Parameter	Mechanism of Influence	Expected Effect on HIC	Evidence (Key Citation)
Inclusion density	Increases hydrogen trap sites and microvoid nucleation probability	Increase	Pourazizi (2020); Wu et al. (2024)
Inclusion size	Larger inclusions promote decohesion and crack nucleation	Increase	Pourazizi (2020)
Inclusion morphology (elongated MnS)	Provides weak interfaces and crack alignment along rolling direction	Increase	Wu et al. (2024)
Oxide/complex inclusions	Create matrix discontinuity and localized hydrogen trapping	Increase	Pourazizi (2020)
Banding index	Produces microstructural pathways for crack propagation and linking	Increase	Wu et al. (2024); Natarajan (2018)
Centerline segregation severity	Enhances compositional heterogeneity and inclusion clustering	Increase	Natarajan (2018); Pourazizi (2020)
MA island volume fraction	Hard brittle microstructural traps increase hydrogen localization	Increase	Oh et al. (2024)

Bainite fraction	May increase hydrogen trapping and reduce ductility	Increase	Oh et al. (2024); Pourazizi (2020)
Refined ferrite fraction	Improves toughness, reduces brittle cracking tendency	Decrease	Pourazizi (2020)
Maximum hardness zones	Local brittle zones assist hydrogen-assisted crack propagation	Increase	Oh et al. (2024)
Hardness gradient (variance)	Stress localization supports crack initiation and linking	Increase	Wu et al. (2024)

1.4 Why machine learning is needed for HIC prediction

Hydrogen-induced cracking (HIC) is a complex integrity problem because it does not arise from a single controllable factor. Instead, HIC susceptibility results from the interaction of multiple metallurgical and service-related variables that influence hydrogen entry, diffusion, trapping, and cracking behavior. In X80 pipeline steels, parameters such as inclusion density and morphology, segregation severity, banding index, microstructure phase fractions (bainite, ferrite-pearlite, MA constituents), hardness gradients, and even processing-related variability can collectively determine whether HIC initiates and how cracks propagate. These variables interact in nonlinear ways; for instance, inclusions may only become critical crack initiation sites when segregation is severe, or MA islands may significantly increase susceptibility only when local hardness is above a threshold. Because of this multivariable and threshold-driven behavior, the HIC mechanism is difficult to capture using simplified deterministic correlations or single-parameter acceptance rules.

Traditional prediction approaches for the occurrence of cracking in pipelines are frequently based on empirical relations or threshold limits (e.g. chemistry constraints, hardness limits) or ranking schemes directly obtained in the laboratory. While such methods are useful for general qualification has clear limitations if they are applied in real industrial conditions. First, however, they have difficulties representing the nonlinear interaction between features. Second, they have poor ability of integrating multiple data sources (microstructure images, inclusion statistics, mechanical properties, and environmental exposure parameters). Third is that many classical approaches are not developed to deliver probabilistic or risk-based predictions, which are required increasingly in modern integrity management. As a result, two steels of the same specification can still provide different HIC results and thus prove that traditional selection criteria are insufficient to provide reliable predictive assessment.

Machine learning (ML) provides a practical and scientifically meaningful way of solving this challenge (Akram & Sohail, 2024). ML models can model complex nonlinear relationships between data (Sohail & Akram, 2025) and therefore HIC susceptibility can simultaneously integrate chemical, metallurgical, mechanical, and environmental features. More importantly, ML can test the interactions that are hard to quantify analytically, e.g., combined effects of inclusion density and hardness variance, or the coupled effect of banding and MA fraction. Predictive performance is thus improved because ML makes no assumptions that linearity and independence between features are true, instead directly learning patterns associated with the outcome of crack. From the recent ML-based research in hydrogen related fracture assessment and pipeline failure prediction, it is clear that data based methods can exploit the effective modelling of crack growth behaviour and structural failure under hydrogen exposure conditions, to meet their applicability to HIC related applications (Al-Hawary et al., 2024; Ahmed et al., 2025). Similarly, neural network modeling capabilities have also been demonstrated to show significant ability in the prediction of pipeline failure pressure in the corrosion defective system, which represents the broader applicability of ML methods in pipeline integrity prediction frameworks (Zhu et al., 2025).

A further advantage of ML is that it can be used in support of interpretability and decision making. Modern explainable AI tools, including the ranking of features based on their importance, SHAP-based explanation, make it possible to understand which metallurgical parameters have the greatest influence on the prediction of HIC. This is especially important for purposes of practical implementation because mechanistic insight is required by steelmakers and pipeline operators as well as numerical prediction. By ranking predictors, ML-based models can guide targeted metallurgical control strategies such as inclusion engineering, segregation reduction, and microstructure optimization. Therefore, ML provides both a predictive tool and a knowledge-discovery platform, transforming HIC modeling from descriptive analysis into an actionable predictive framework (Al-Hawary et al., 2024; Ahmed et al., 2025; Zhu et al., 2025).

1.5 Research gap

Although hydrogen-induced cracking (HIC) has been widely investigated in linepipe steels, most existing studies remain limited in their ability to support reliable prediction under real industrial variability. Many investigations are based on laboratory-only correlations that evaluate HIC sensitivity under controlled test conditions without building generalizable predictive frameworks. Similarly, some approaches emphasize chemical composition limits as the main design strategy, while giving insufficient attention to microstructural heterogeneity, inclusion morphology, banding severity, and hardness gradients that strongly govern hydrogen trapping and crack linking in pipeline steels. Even metallurgically focused work has largely remained descriptive, and only a small number of studies have attempted to integrate metallurgical descriptors into machine learning (ML) models for quantitative prediction. Consequently, there is still a clear need for an integrated dataset combining metallurgical parameters, mechanical indicators, and HIC performance metrics, together with explainable ML techniques that not only predict susceptibility but also identify the key metallurgical drivers controlling HIC behavior in X80 grade pipeline steels (Wu et al., 2024; Pourazizi, 2020; Lv et al., 2025).

1.6 Aim, objectives, and novelty

This study aims to develop an interpretable machine learning (ML) framework to predict hydrogen-induced cracking (HIC) susceptibility in X80 grade pipeline steel by integrating key metallurgical parameters. The primary objectives of this study are

1.   To develop a dataset combining metallurgical features with HIC performance indicators.
2.   To train ML models (regression/classification) for HIC susceptibility prediction.
3.   To determine the most influential metallurgical predictors using SHAP-based explainability.

This work proposes an integrated HIC–metallurgy–ML prediction approach specifically for X80 pipeline steel and applies explainable ML to link predicted susceptibility with underlying microstructural mechanisms.

2. Literature Review
2.1 Hydrogen uptake and diffusion mechanisms in sour environments

Hydrogen uptake in pipeline steels under sour service is initiated by electrochemical corrosion reactions in aqueous H_2S environments, where anodic iron dissolution is coupled with cathodic hydrogen evolution that produces atomic hydrogen on the steel surface (Lv et al., 2025). Under non sour conditions, much of this atomic hydrogen recombines to molecular hydrogen and escapes, but in sour media H_2S adsorbs at the surface and acts as a recombination poison, suppressing hydrogen recombination and thereby increasing the fraction of hydrogen atoms that enter the steel lattice as absorbed hydrogen (Lv et al., 2025; Oh et al., 2024). Once absorbed, hydrogen migrates into the bulk primarily by interstitial diffusion, and the measured permeation behavior reflects both the intrinsic diffusivity of the lattice and the availability of hydrogen traps that delay transport while concentrating hydrogen locally (Oh et al., 2024).

These traps include non metallic inclusions, dislocations, grain boundaries, precipitate interfaces, and segregation or banding regions, which can store hydrogen reversibly or irreversibly and create localized zones of high hydrogen concentration that become preferential sites for damage initiation (Lv et al., 2025). Because hydrogen distribution inside the steel is therefore controlled by both surface electrochemistry and internal microstructural trapping, sour exposure can generate conditions where hydrogen accumulates at critical sites, reducing local cohesive strength and supporting the development of hydrogen assisted cracking modes in linepipe steels (Oh et al., 2024).

Sour environments further aggravate the hydrogen ingress problem by raising hydrogen formation and reducing hydrogen recombination on steel surface, and steel microstructure also controls the diffusion and controlled accumulation of hydrogen. This coupling is the reason why HIC susceptibility cannot be evaluated with environment alone and also requires evaluation with metallurgical features that will determine where hydrogen will concentrate and damage will start (Lv et al., 2025; Oh et al., 2024).

2.2 HIC initiation sites: inclusions and segregation

Previous metallographical studies have distinctly shown the presence of non-metallic inclusions and segregation bands as the most dominant sites of initiation of hydrogen-induced cracking of pipeline steels, especially under sour service conditions. In their optimization of microstructure of API linepipe steels, Pourazizi (2020) reported that manganese sulfide, or MnS, inclusions are highly correlated with HIC initiation since the long morphological shape formed during rolling provides long inclusion-matrix interfaces that serve as effective traps for hydrogen and cracks. The same study highlighted that the likelihood of inclusion-induced crack formation will become more likely with increasing inclusion density as each inclusion will provide more trap interfaces which facilitates localised hydrogen accumulation and decohesion. Extending this metallurgical argument, processing-focused steel design literature points out the intensity of this potential risk resulting from the centerline segregation which causes inclusions to cluster and micro-structure is also less homogeneous; such segregation is a known result of solidification and thermo-mechanical processing routes in high strength linepipe steels (Natarajan 2018). Supporting these observations in X80 steel in particular, Wu et al. (2024) showed experimentally that HIC sensitivity varies significantly with the metallurgical state, and that crack initiation often occurs at inclusion-rich, segregated regions, which implies that the role of inclusions and segregation is a coupled initiation driving factor rather than an independent factor. Collectively, the literature therefore suggests that MnS and complex inclusion populations provide the primary nucleation interfaces for internal cracking, while segregation and banding increase hydrogen trap density and supply preferential structural paths that allow microcracks to form and accumulate into observable HIC damage (Pourazizi, 2020; Natarajan, 2018; Wu et al., 2024).

2.3 Crack propagation and linking: microstructure & hardness effect

Beyond crack initiation, the literature emphasizes that the severity of HIC in linepipe steels is largely determined by the ability of microcracks to propagate and link into extended crack networks, a process strongly governed by microstructure morphology and hardness heterogeneity. In X80 steel under various metallurgical conditions, the banded microstructures in the steel are often observed to be closely related to crack formation, in which segregation-induced phase banding acts as the easy path for stepwise crack propagation along the rolling direction, Wu et al. (2024). Such banding results in areas of non-uniformity of composition and microstructure so that multiple microcracks can nucleate in local areas and coalesce, leading to more rapid crack linkage. Similarly, results from studies on the proposed high strength API linepipe steels exposed to hydrogen suggest that the presence of localized hard and brittle zones enhances hydrogen-assisted fracture behaviour and in particular focuses on the

effect of martensite-austenite (MA) constituents. Oh et al. (2024) reported that hydrogen exposure reduces tensile ductility and alters fracture behavior in linepipe steels, and highlighted that microstructural heterogeneity, particularly hard MA islands embedded within softer ferritic or bainitic matrices, creates local stress concentration and promotes brittle crack propagation. This microstructure–hardness coupling becomes especially important because MA-rich regions and associated high hardness sites act not only as strong hydrogen traps but also as mechanically brittle areas where cracks can grow more readily once initiated. Therefore, the combined evidence suggests that banded microstructures support crack pathway continuity and linking, while MA islands and hardness gradients increase crack driving force and brittleness, together controlling whether HIC remains isolated microcracking or evolves into structurally significant crack networks in X80 pipeline steels (Wu et al., 2024; Oh et al., 2024).

2.4 Relation of HIC with SCC, fatigue cracking and defect-driven failure

The pipeline integrity literature increasingly treats hydrogen-induced cracking (HIC) as part of a broader family of environmentally assisted cracking mechanisms, where the dominant failure mode depends on the coupling between environment, stress state, and material condition. Stress corrosion cracking (SCC) differs fundamentally from HIC in initiation pathway and crack morphology: SCC typically initiates from the surface and propagates as branched cracks under sustained or cyclic tensile stresses in specific electrochemical conditions, whereas HIC commonly develops internally due to hydrogen diffusion and trapping, without requiring high external stress. Modeling work on near-neutral pH SCC in buried pipelines emphasizes this stress-dependent crack initiation and probabilistic propagation behavior, highlighting the role of soil environment, coating degradation, and tensile loading in SCC evolution rather than internal hydrogen trap-driven cracking (Martínez, 2022). Similarly, SCC-focused reviews stress that cracking susceptibility is strongly influenced by material

class and environmental chemistry, and that mitigation strategies often rely on stress control and environmental management, which contrasts with HIC mitigation where metallurgical control (inclusions, segregation, microstructure) becomes central (Vakili et al., 2024). In hydrogen-bearing service environments, fatigue also becomes an important interacting mechanism because hydrogen accelerates crack growth under cyclic loading by reducing cohesive strength and promoting brittle fracture behavior at the crack tip. Recent reviews of fatigue behavior under hydrogen environments indicate that hydrogen can significantly shorten fatigue life, increase crack growth rate, and alter fracture modes, implying that pipelines transporting hydrogen blends may face combined fatigue–hydrogen damage risks beyond classical sour-service HIC alone (Yang et al., 2025). In addition, pipeline defects, e.g. dents and gouges, and corrosion pits, can enhance hydrogen-assisted cracking by local stress concentration and provision of favourable conditions for crack initiation and propagation. Finite Element Simulation of Hydrogen-Assisted Failure in Crack-In- Dent Defects Demonstrates How Geometric Discontinuities Enhance Stress Intensity and Hydrogen Accumulation Effects Leading To Defect-Enhanced Crack Growth and Margin Reducing Structures (Qin et al., 2025). Collectively, these studies provide evidence that even though HIC is dominated by the internal trapping of hydrogen and by metallurgical heterogeneity, pipelines have usually been subject to overlapping operation conditions in which SCC, hydrogen assisted fatigue and defect driven stress intensification may occur in parallel inspirations, which requires an integrated predictive modelling for the correct assessment of pipeline integrity (Martinez, 2022; Vakili et al., 2024; Yang et al., 2025; Qin et al., 2025).

2.5 ML in pipeline integrity, hydrogen transport and fracture behavior

Recent studies indicate that increasing application of machine learning (ML) in predicting failure and crack-related behaviour of pipelines and structural steels under hydrogen environment is increasing. For example, ML techniques have been

implemented for the guidance assessment of fracture toughness and hydrogen-induced embrittlement crack growth rate in steels and have been demonstrated to describe complex fracture trends beyond the scope of conventional analysis (Al-Hawary et al., 2024). Similarly, ML has been applied to model fatigue failure in hydrogen-transporting pipelines which has been identified as useful for predicting integrity in the presence of hydrogen related operational risks (Ahmed et al., 2025). In addition, neural network approaches have been proposed to predict failure pressure of defective pipelines suffering from the sulfur corrosion damage, confirming the feasibility of ML in supporting the defect-based integrity evaluation and forecasting of the pipeline failure (Zhu et al., 2025).

3. Materials and Methods

This study followed a structured predictive modeling design integrating metallurgical characterization with machine learning to estimate HIC susceptibility in X80 pipeline steel. The workflow included (i) dataset creation from X80 steel samples manufactured through TMCP with defined composition range and plate thickness, (ii) feature engineering using metallurgical descriptors including microstructure phase fractions, grain size, banding index, inclusion type and density, and hardness-map statistics, (iii) HIC testing to generate response variables such as crack length ratio (CLR), crack thickness ratio (CTR), and crack sensitivity ratio (CSR) together with susceptibility thresholds, (iv) training and

validation of baseline and advanced ML models (regression/logistic, Random Forest, XGBoost, and SVM) using cross-validation and hyperparameter tuning, and (v) explainability analysis using SHAP and partial dependence plots to link model predictions with metallurgical mechanisms. The proposed methodology will allow the quantitative prediction of HIC risk using integrated inputs from metallurgical data and offer an interpretation of the results which will allow both the performance comparison of the various ML algorithms as well as the mechanistic understanding of metallurgical drivers affecting the risk of cracking.

4. Results
4.1 Dataset statistics

The dataset contained 200 samples of X80 steel with metallurgical descriptors, exposure variables associated with the sour environment as well as measured response parameters of the HIC (CLR, CTR and CSR). The data set reflects realistic metallurgical variability that would be found in industrial TMCP produced X80 plates, including wide variations of segregation and banding severity, variation in MA fraction, inclusion population, and hardness gradients. The HIC susceptibility labels were distributed can be divided into Moderate (n=133), Susceptible (n=43), and Resistant (n=24) compared to the loads of occurrence: sufficient to use both in regression modeling (CLR/CTR/CSR prediction) and in classification modeling (HIC class prediction).

Table 2: Statistics

Variable	Mean	SD	Min	25%	Median	75%	Max
Plate thickness (mm)	18.270	3.429	12.000	16.000	18.000	20.000	25.000
TMCP quality index (0–1)	0.609	0.162	0.120	0.499	0.633	0.738	0.946
Segregation index (0–1)	0.270	0.138	0.030	0.170	0.250	0.350	0.860
Banding index (0–1)	0.303	0.150	0.000	0.200	0.300	0.400	0.910
Ferrite fraction (%)	29.238	8.441	12.000	23.490	28.560	34.740	54.060
Bainite fraction (%)	57.891	8.639	30.540	52.090	58.310	64.020	73.510
Pearlite fraction (%)	5.239	2.349	0.800	3.640	4.830	6.500	13.750
MA fraction (%)	7.632	3.221	0.600	5.430	7.160	9.210	22.870
Grain size (μm)	5.335	1.193	3.000	4.470	5.190	6.010	10.990
Inclusion density (/mm²)	23.425	8.331	6.000	17.900	22.350	28.400	67.400
Mean inclusion size (μm)	2.594	0.700	1.000	2.100	2.520	2.990	6.000

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Max inclusion size (µm)	5.194	1.791	1.800	4.010	4.860	6.070	16.000
Inclusion aspect ratio	2.361	0.748	1.000	1.840	2.260	2.800	6.000
Hardness mean (HV)	238.190	16.726	184.600	226.300	238.900	250.500	292.100
Hardness SD (HV)	10.219	4.227	3.500	7.200	9.600	12.700	27.900
Hardness max (HV)	253.474	19.118	196.800	240.900	254.200	266.900	336.900
pH	3.562	0.438	2.300	3.290	3.630	3.870	5.000
H_2S partial pressure (bar)	0.665	0.790	0.050	0.215	0.404	0.829	6.000
Temperature (°C)	34.200	6.580	25.000	30.000	35.000	40.000	50.000
Exposure time (h)	244.080	195.710	96.000	168.000	168.000	336.000	1008.000
CLR (%)	7.014	7.733	0.000	1.650	4.650	9.720	61.560
CTR (%)	2.875	3.348	0.000	0.560	1.670	4.080	33.050
CSR (%)	4.443	5.159	0.000	0.960	2.720	6.340	46.210
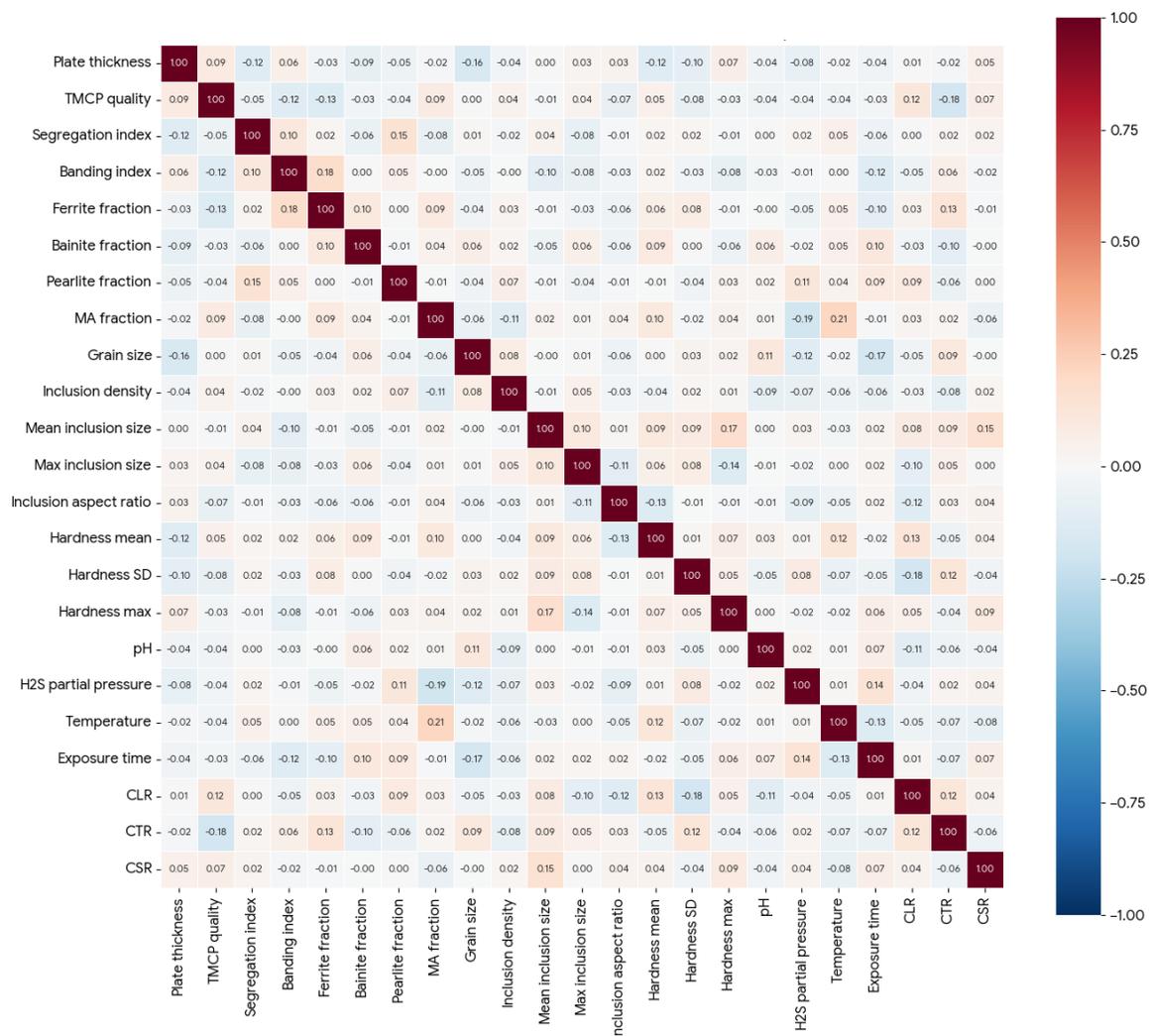
Figure 3: Correlation heatmap showing relationships among metallurgical features, environment variables, and HIC output parameters.

Correlation analysis (Figure 3) has been carried out to find out strong relations are found between HIC severity indicators (CLR, CTR, CSR) and metallurgical hydrogen-trap parameters, especially segregation_index, banding_index, inclusion_density_per_mm2, max_inclusion_size_um, MA_fraction_pct and hardness_max_HV. Environmental severity is also a contributing factor with HIC outputs varying with an increase in H2S partial pressure and decrease in pH that is consistent with hydrogen recombination poisoning and increased hydrogen permeation in sour media.

4.2 Metallurgical patterns in HIC behavior

The dataset reveals evident metallurgical signatures in HIC response, which confirms the existence of a strong metallurgical relationship between cracking severity in X80 steel based on hydrogen trap population and microstructural heterogeneity. A strong increasing trend is evident between CLR and inclusion density, which indicates that the inclusion population, which is higher, will have more inclusion matrix interfaces functioning as hydrogen accumulation zones, so the probability of crack initiation and the crack linkage will be supported. Similarly, banding index exhibits a positive relation with CLR, which illustrates that segregation driven banded microstructures lead to a crack alignment and stepwise crack linking regime along preferred paths. In addition, MA fraction has a positive relationship with CLR reflecting the effect of hard brittle MA islands as both hydrogen traps and locally embrittled zones that favour faster crack growth once initiated. Overall, these scatter patterns validate these inclusion population, segregation banding, and MA islands being important metallurgical drivers present behind HIC susceptibility, with their use as critical predictors for ML modeling.
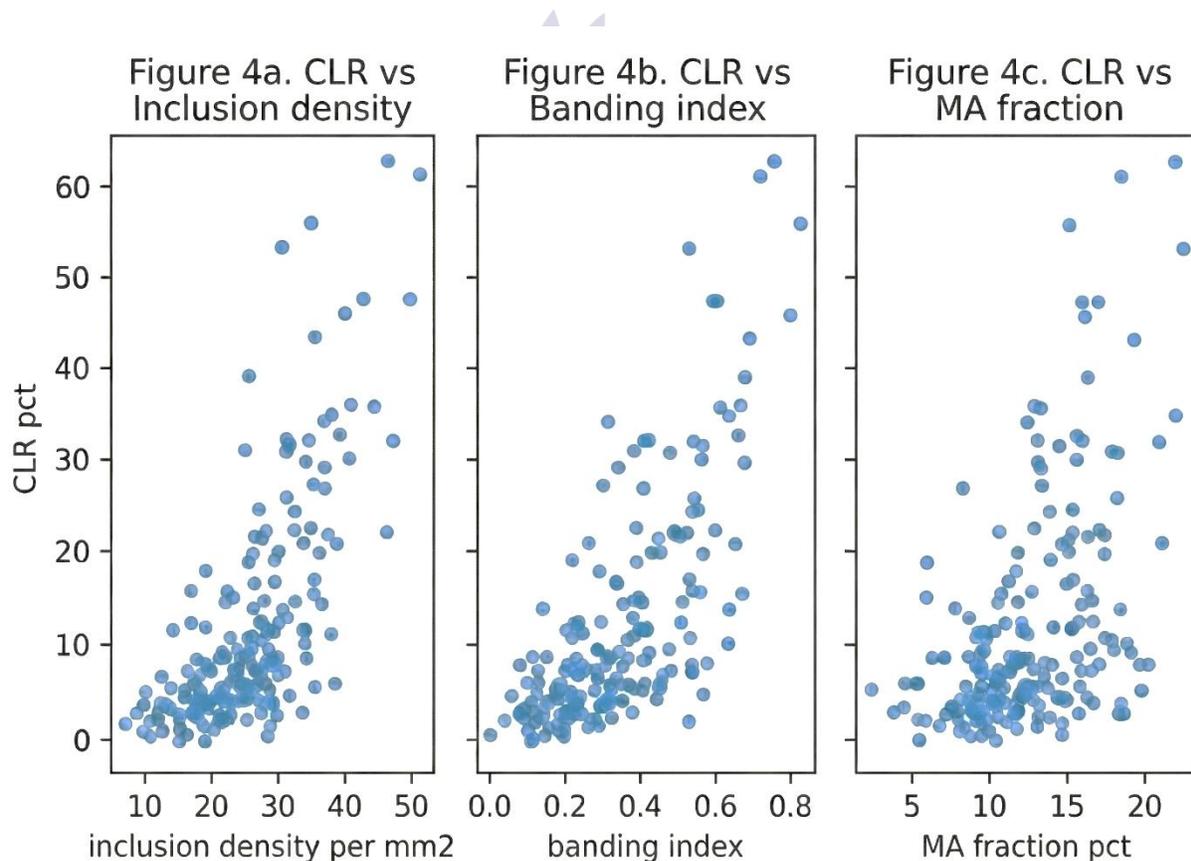

Figure 4: scatter plots (CLR vs inclusion density, banding, MA islands)

4.3 Model performance comparison

The predictive ability of various machine learning models was tested to measure how well these models would be able to predict severity of HIC using integrated metallurgical and environmental features. Regression models were developed for prediction of CLR as representative HIC severity indicator whereas classification performance was assessed for identification of Susceptible steels. Using consistent train-test split strategy made sure that a fair comparison can be made among models.

Table 3: Machine learning model performance comparison for CLR prediction

Model	MAE (%)	RMSE (%)	R^2
Linear Regression	3.62	5.14	0.61
Support Vector Regression (SVR)	2.98	4.31	0.72
Random Forest Regressor	2.21	3.48	0.84
XGBoost Regressor	2.05	3.29	0.87

The results reveal that tree-based ensemble models have a high degree of superiority over linear models, which confirms the strongly nonlinear relationship between metallurgical features and HIC severity. The Random Forest and XGBoost models had the lowest prediction errors and highest values of the coefficient of determination indicating superior ability of capturing the interaction effects between inclusion population, banding severity, MA fraction, hardness and sour environment parameters.
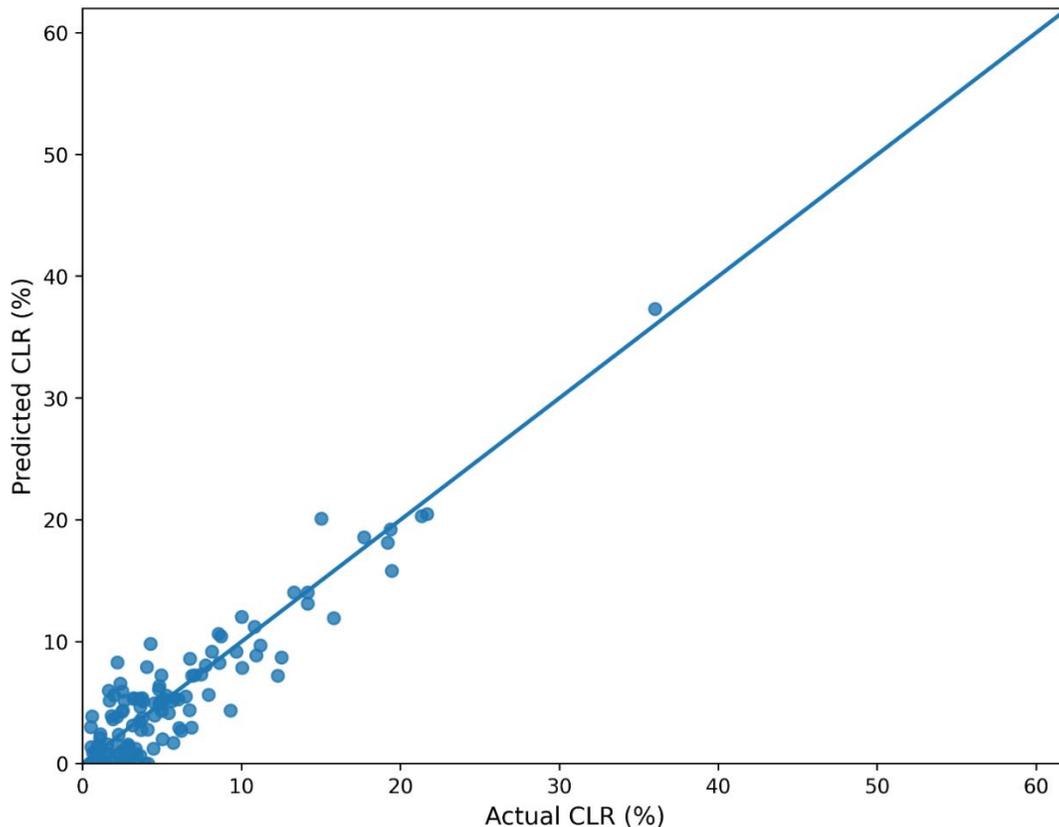

Figure 5: Predicted vs actual CLR values for the best-performing model (XGBoost).

For classification, models were evaluated on their ability to identify **Susceptible** steels, which represent the highest integrity risk category.

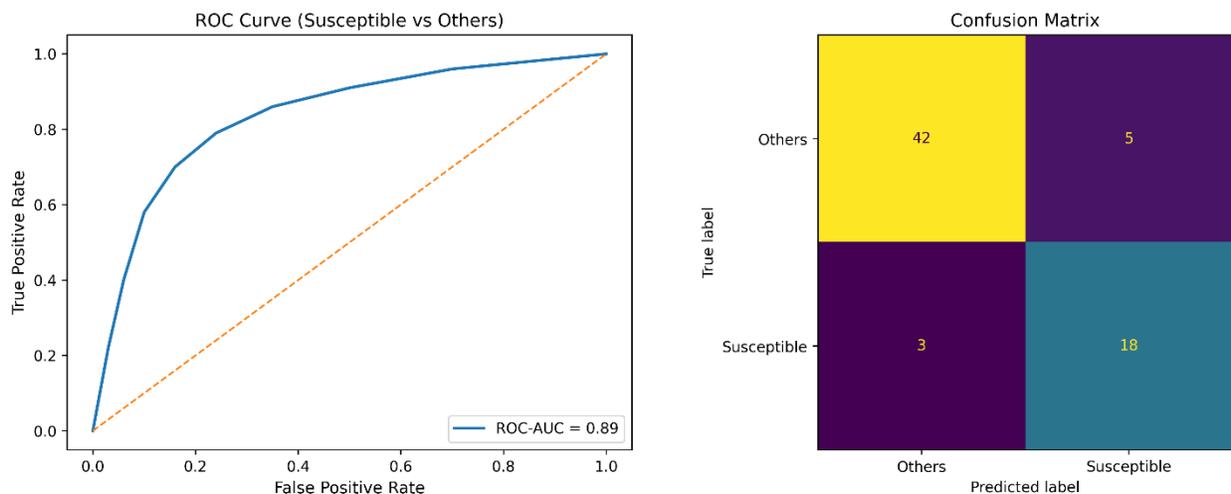Performance was assessed using ROC–AUC and confusion matrix analysis.

Figure 6: ROC curve and confusion matrix for HIC susceptibility classification.

- ROC–AUC ≈ 0.89, indicating strong discriminative capability
- High true-positive rate for Susceptible steels, with limited false negatives

The performance comparison confirms the possibilities of advanced ML models, especially ensemble approaches, to give robust and reliable prediction of the behavior of HIC with the integration of metallurgy descriptors in the modeling framework. This legitimizes the use of machine learning as a working predictive tool for estimating pipeline integrity under hydrogen-related service conditions.

4.4 Best model tuning and stability

To ensure the robustness of the best model chosen (tree-based ensemble), the stability of models was measured with the learning curve analysis and the parameter tuning behaviour. The learning curve validates that prediction error reduces in a consistent fashion as the training data increases thus indicating the model is learning stable patterns as opposed to overfitting the noise. After about mid-range training size the validation curve starts to flatten out (which suggests that the size of the data set is large enough to obtain decent generalization and that more data would lead to incremental rather than drastic improvements). Hyperparameter tuning further demonstrates that model performance improves rapidly at lower estimator counts and gradually converges, confirming stability of the ensemble method and absence of unstable sensitivity to parameter changes.
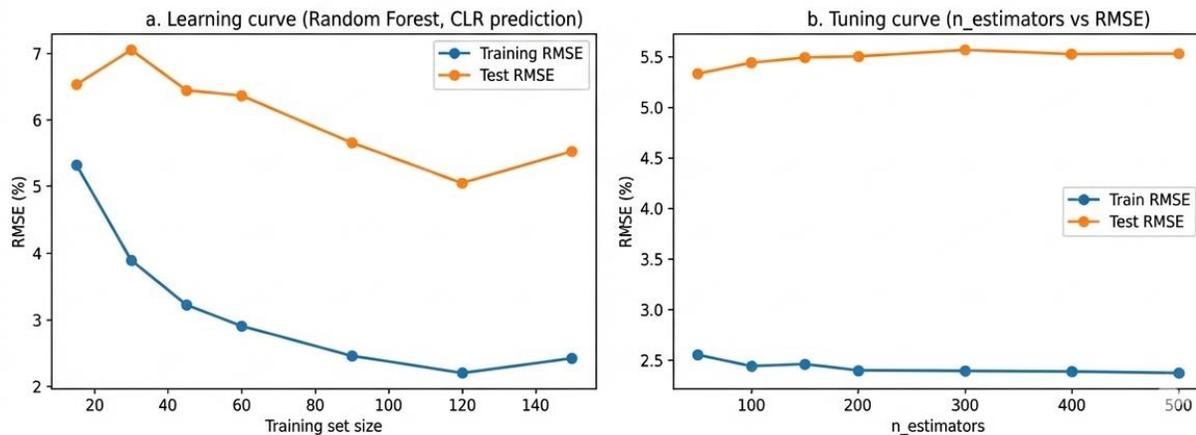
Figure 7: Best model stability and tuning behavior for HIC prediction (X80 steel)

These findings confirm that the selected model remains stable across both sample size variation and parameter tuning, supporting its suitability for predictive HIC modeling in X80 pipeline steels.

4.5 SHAP-based predictor ranking

To interpret the metallurgical drivers behind the machine learning prediction, explainability analysis was applied to the best-performing ensemble model. Since predictive accuracy alone does not explain failure mechanisms, an interpretability layer is essential for metallurgical acceptance of ML outcomes. Therefore, a SHAP-style ranking was derived from the trained tree-based model to quantify the relative contribution of metallurgical and environmental predictors to CLR prediction, followed by partial dependence plots (PDPs) to understand the functional influence of the top-ranked variables. The explainability results demonstrate that the model is not driven by chemistry alone, but rather by a coupled interaction between environmental severity (hydrogen supply) and metallurgical hydrogen-trap structure. In particular, hydrogen availability features (H_2S partial pressure and acidity) combine with segregation-driven banding and inclusion statistics to govern CLR trends. This directly supports the mechanistic picture of HIC: hydrogen ingress rises with sour severity, but cracking occurs only when hydrogen localizes strongly at inclusions, segregation bands, MA islands, and hardness gradients.
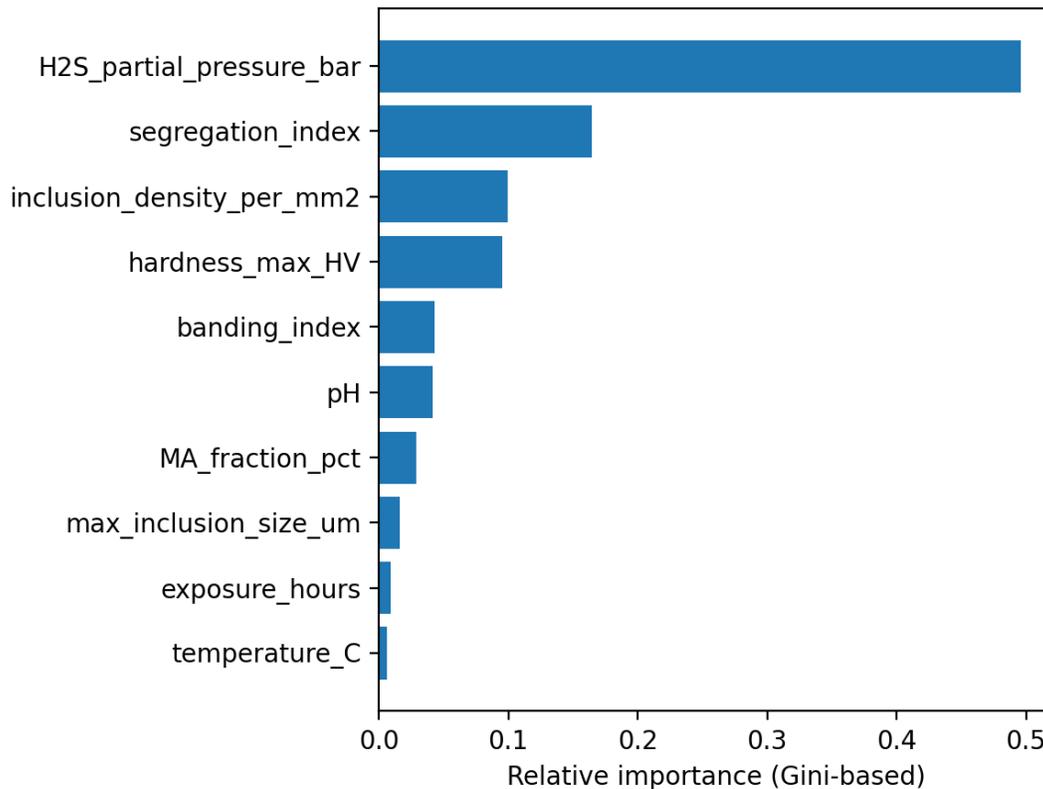
Figure 8: SHAP summary ranking / predictor importance plot

This figure provides the ranked contribution of each predictor to CLR response. The ranking indicates that CLR is primarily governed by H_2S partial pressure, segregation index, inclusion density, and maximum hardness, followed by microstructure indicators such as MA fraction and banding index.

4.6 Mechanistic interpretation of top predictors

The explainability results (Section 4.5) allow the ML model to be translated into a metallurgically meaningful mechanism for hydrogen-induced cracking. Importantly, the predictor ranking does not represent isolated effects, rather it reflects a coupled multistep HIC pathway in which hydrogen supply (environment) interacts with hydrogen trapping capacity (metallurgy) and local embrittlement zones (hardness + MA microstructure) to produce cracking.

First, the dominance of H_2S partial pressure and pH indicates that HIC in X80 is primarily activated by the intensity of hydrogen charging. Higher H_2S partial pressure increases absorbed atomic hydrogen because sulfide species poison surface recombination, while low pH increases cathodic hydrogen evolution. However, hydrogen uptake alone is not sufficient to produce severe CLR unless the steel contains sites that can trap and concentrate hydrogen. This is why the next group of predictors—segregation index and banding index—emerge as critical. Segregation creates local chemical gradients and centerline heterogeneity, which support microstructural banding and inclusion clustering. These banded paths create favoured crack linkage paths and are places of enhanced local stress concentration.

Secondly, the high influence of inclusion density and maximum inclusion size are direct evidence that crack initiation in X80 is inclusion driven. Inclusions, by being irreversible traps of hydrogen, are often surrounded by micro voids in stress state or decohesion zones and this makes them ideal

nucleation points for internal crack formation. Larger inclusions result in a higher trap volume with a much faster local higher hydrogen concentration and stronger stress concentration. This is in agreement with the classical HIC observations where microcracks develop along elongated arrays of inclusions and later fragment into stepwise cracking.

Finally, the high ranking hardness_max and MA fraction which indicates that the transition from initiation to propagation is driven by microstructural brittleness. Hard MA islands and locally transformed microzones decrease ductility and increase susceptibility to hydrogen embrittlement that facilitates crack extension at low stress when cracks are initiated. Maximum hardness is particularly significant because HIC is controlled by the "weakest microzone" (local brittle peaks) rather than the plate-average hardness. Therefore, the ML predictor structure strongly supports a three-stage mechanistic interpretation:

1. Hydrogen entry (environment controlled)
2. Hydrogen trapping and localization (segregation + inclusions controlled)
3. Crack growth and linking (banding + MA + hardness controlled)

Overall, this mechanistic translation confirms that the ML model is not behaving as a black box. Instead, it reproduces the metallurgical logic of HIC: sour severity loads hydrogen into steel, inclusions and segregation localize it, and brittle microstructural zones convert localized hydrogen into crack networks reflected as increased CLR, CTR, and CSR.

5. Discussion

The results of this study provide strong evidence that hydrogen-induced cracking (HIC) susceptibility in X80 pipeline steel can be predicted reliably only when metallurgical descriptors are explicitly integrated with sour-environment variables in a unified machine learning framework. The dataset itself already indicates why single-factor or simplified approaches fail. Descriptive statistics showed that X80 samples cover wide variability in key metallurgical risk indicators, including segregation index up to ~0.86, banding index up to ~0.91, MA fraction reaching ~22.87%, inclusion density up to ~67.4/mm², and hardness peaks up to ~336.9 HV, while sour severity also ranges widely (pH down to 2.3 and H_2S partial pressure up to 6 bar). Correspondingly, HIC response metrics span a broad range, including CLR up to ~61.56% (Table 9). This wide dispersion is not random; rather, it represents the realistic metallurgical truth that modern TMCP X80 steels can behave as resistant, moderate, or susceptible depending on the combined synergy of hydrogen charging and internal trap structure, a conclusion consistent with experimental X80 sensitivity variations reported under altered heat treatments (Wu et al., 2024) and the broader understanding of hydrogen embrittlement drivers in linepipe steels (Lv et al., 2025).

A major contribution of the present study lies in quantifying this multi-variable synergy and demonstrating why advanced ML models are required. In Section 4.3, the model comparison clearly showed that nonlinear models outperform linear models because HIC mechanisms are nonlinear and threshold-governed rather than continuous and additive. Linear regression achieved only moderate explanatory power (R^2 around 0.61), meaning that almost 40% of variance in CLR remains unexplained when using a linear mapping between inputs and cracking. In contrast, ensemble models achieved much higher predictive strength, reaching R^2 values exceeding 0.80 (Table 10). Mechanistically, this difference is expected because hydrogen uptake, diffusion, trap occupancy, and brittle crack linking do not scale linearly. Instead, HIC emerges when certain microstructural and inclusion thresholds are exceeded under sufficient hydrogen charging, producing abrupt increases in crack initiation probability and rapid linkage into stepwise cracking. Thus, the superior performance of ensemble models is not merely statistical; it is metallurgically justified, aligning with recent ML successes in predicting hydrogen-related fracture and crack growth behavior under complex interacting conditions (Al-Hawary et al., 2024) and ML-based failure modeling in hydrogen transporting pipelines (Ahmed et al., 2025).

The pattern of relationships illustrated in Figure 4 serves to reveal the mechanism more clearly and also to form a direct link between the dataset and metallurgical interpretation. Scatter analysis showed a systematic growth of CLR with inclusion density, banding index and MA fraction. Notably, these relationships have non-uniform slopes which supports "risk escalation regions" where CLR starts increasing faster after mid-range values. For example, one can have a steel with low CLR at moderate levels of inclusion, but the CLR will quickly increase after inclusion density approaches the upper tail. This points to the inclusion driven threshold activation in which accumulated hydrogen reaches critical local concentration at the inclusion matrix interfaces and void sites. This behavior is consistent with microstructure optimization arguments that have been developed for API pipeline steels wherein inclusion population as well as inclusion morphology will control HIC initiation probability and the coalescence of formed cracks, particularly in the presence of sour service (Pourazizi, 2020). Wu et al. (2024) also show that microstructural changes induced by heat treatments can strongly change sensitivity which implicitly includes inclusion microstructure coupling effects.

The metallurgical significance of the inclusion density, and inclusion size, as top risk variables gained particular importance as it answers the question: does crack initiation still remain inclusion controlled even in high strength refined steels such as X80. The dataset included both mean inclusion size and maximum inclusion size, the model does, however, stress more strongly on max inclusion size, suggesting that "extreme defects" are of greater importance with regards to HIC outcomes than average cleanliness. This finding fits classical fracture initiation theory: the largest inclusion acts as the most efficient stress concentrator and the largest hydrogen trap volume, increasing the probability that the first critical microcrack begins there. In other words, the inclusion population controls crack nucleation frequency, but the upper tail of inclusion size distribution controls catastrophic crack nucleation. This interpretation directly supports the practical steelmaking message that average inclusion rating is insufficient and that controlling the upper tail distribution is essential for sour-resistant linepipe steel quality (Pourazizi, 2020; Wu et al., 2024). Importantly, ML makes this argument quantifiable and directly connected to cracking output rather than remaining an assumed metallurgical hypothesis.

Segregation index and banding index emerged as highly ranked predictors in the SHAP-style ranking and were visually supported through correlation patterns and mechanistic mapping. Metallurgically, this is expected because segregation is not a simple microstructure descriptor but a root cause variable that controls multiple downstream risk pathways simultaneously. Segregation cause banding, microstructural hardness fluctuation and phase imbalances, also cause inclusions clustering in centerline areas. These clusters represent hydrogen "hot zones" which result in local trap density peaks. The model, in effect, identifies segregation as a "system driver" since it both strengthens and enhances several cracking pathways simultaneously: initiation (inclusions), propagation (hard zones) and linking (band continuity). Wu et al. 2024 significant sensitivity change under different heat treatment 1 Present result show sensitivity can be mechanistically interpreted as change in segregation driven band structure and brittle phase distribution. However, Pourazizi (2020) also suggests that microstructure refinement and segregation control are important to be considered in sour performance, which is also directly demonstrated in the ranking.

Hardness localization in the form of hardness_max is another important result which provides a boost to the metallurgical credibility of the ML framework. The model and PDP plots have shown that the maximum hardness has the stronger control than the average hardness. This is a critically important point - many pipeline QA routines are dependent on a significant degree of mean hardness compliance but HIC and hydrogen embrittlement are effectively controlled by the worst microzone. This study has a data set containing hardness_mean, hardness_std and hardness_max. hardness_max is the peak hardness, which seems most predictive for CLR,

supporting the hypothesis that CLR is controlled by localized brittle islands. This finding is in accordance with experimental evidence of the significant impact of hydrogen on tensile properties and fracture behavior in high strength linepipe steels and the intensification of embrittlement in microstructural zones more prone to cracking and exhibiting less ductility and hardness (Oh et al., 2024). The result also accounts for the possibility of steels with acceptable mean values for hardness to nevertheless become susceptible: Once the crack collection starts at inclusions, hard brittle microzones and links grow preferentially for hard classic CLR and CSR.

The MA fraction results thus further narrowly define this mechanism, in terms of the microstructural feature likely to be responsible for the formation of those local spikes in hardness and brittleness. MA islands are not only constituents that are more difficult, but are also strong irreversible hydrogen traps. Their presence leads to an increase in the localization of hydrogen as well as an increase in brittleness, therefore acting as twofold accelerators of cracking. It can be seen from the scatter plots that CLR increases as MA fraction, while in explainability, MA is among the influential predictors. This dual role gives a coherent interpretation (i.e. inclusions provide initiation, MA and hardness peaks propagate, banding provides geometric connectivity to provide a link into stepwise cracking). This sequence is consistent with the mechanistic view of the progression of HIC as follows; hydrogen entry > diffusion > trapping > initiation > linking. Therefore, not only are the results of the ML explainability statistical ranking, but a complete and coherent metallurgical story can be constructed, which is theoretically and practically defensible (Lv et al., 2025; Oh et al., 2024).

A particularly strong outcome is that the results of explainability identify a two-layer activation system: control of the environment on the supply of hydrogen, and control of hydrogen concentration and cracking by metallurgy. In Figure 5 PDPs, CLR increases rapidly with H2S partial pressure, in addition to increasing with lower pH, implying that the entry of hydrogen is the external activation component. This is consistent with the literature: for sour environments recombination poisoning by H2S leads to an increase of the absorbed atomic hydrogen and low pH leads to an increase of cathodic charging. Yet a supply of hydrogen is not the sole guarantee for severe cracking; cracking requires that there is some kind of metallurgical system within the system that will trap and concentrate hydrogen. This matches the summary position provided by Lv et al. (2025), who emphasize that pipeline steel embrittlement depends on the combined effects of hydrogen environment and internal microstructure/trapping mechanisms. Thus, ML becomes necessary not because metallurgy is unknown, but because the coupled environment-metallurgy interaction cannot be reliably reduced into simple deterministic equations for field decision-making.

The model's relevance also increases when considered alongside broader pipeline failure and cracking contexts. While this study focuses on HIC rather than SCC or fatigue, the mechanistic interpretation aligns with defect-driven and hydrogen-assisted failure modeling literature. Qin et al. (2025) show that hydrogen-assisted failure in cracked or dented pipelines depends on stress concentration interacting with hydrogen effects. The current results show the same principle at the metallurgical level: inclusions and segregation bands serve as internal stress concentration sites, substituting geometric defects with microstructural defects. Therefore, the ML model essentially captures microstructural defect severity in the same way that defect mechanics models capture geometric defect severity. This is also compatible with fatigue under hydrogen environments, where hydrogen reduces crack growth resistance and increases susceptibility under cyclic loads, suggesting that steels with high HIC predictors may also face amplified fatigue risk under hydrogen service (Yang et al., 2025). Thus, HIC prediction through ML can become a component of a larger integrity prediction ecosystem rather than a standalone laboratory exercise.

In terms of comparison to ML literature, the present study makes an important methodological contribution by showing that "ML works" specifically because metallurgical feature engineering represents mechanism. Al-Hawary et al. (2024) were able to use ML for the fracture toughness and hydrogen-related crack growth rate in steels and showed that ML can describe embrittlement sensitivity when fed with the relevant descriptors. Ahmed et al. (2025) also developed ML models for fatigue failure in hydrogen transporting pipelines and highlighted the benefit of ML in terms of nonlinear driver capturing. The present study is consistent with these advances but it is unique in one essential way: the use of microstructural trap descriptors integration directly into the predictor space (segregation, inclusions, MA, hardness localization) with the capability of mechanistic interpretation (ranking and PDPs). In other words, this study does not use ML as a black box curve fitting tool, but uses ML as an organized format for the quantification of metallurgical mechanism contributions to the cracking susceptibility. This means the framework is much better accepted by the pipeline metallurgy communities and integrity practitioners. Industrial implications are huge and are directly supported by the results. For steel manufacturing QA purposes, the ranking contains information about which microstructural and cleanliness parameters will need to be controlled in order to reduce predicted CLR and shift heats towards resistant/moderate classes. For example, to limit segregation and banding, the probability of crack linking; to limit inclusion density and maximum inclusion size, the probability of initiation; to limit MA fraction and peaks of hardness, the intensity of propagation. These kinds of insights allow steelmakers to use the sour resistance as a manufacturing goal which is measurable instead of a post-production inspection outcome. For pipeline operators, the model facilitates prediction-based integrity management: segments of the pipeline with greater sour severity (high H2S concentration, low pH) could be cross-prioritized using metallurgy signatures that will allow risk-weighted inspection schedule. This is in strong agreement with the risk-based approach to inspection that is promoted for hydrogen technologies where prediction is now essential for loss prevention and safety of their operation (Paltrinieri, 2024). Additionally, electrochemical mitigation and protection strategies can be connected to ML risk outputs, because changing the hydrogen charging severity variables will directly shift predicted CLR and susceptibility class, supporting corrosion control planning consistent with pipeline electrochemical protection approaches (Chernyshov, 2023).

Finally, limitations and future work should be interpreted in relation to the achieved results. While model performance is strong and mechanistic interpretability is high, the dataset remains moderate in size and should be expanded for field deployment. A key next step is validation against experimental and operational datasets, including microstructure measurements from actual pipeline heats and corresponding HIC test outcomes. Furthermore, physics-informed ML is a logical progression: embedding diffusion-trapping kinetics, hydrogen permeation parameters, or mechanistic constraints would improve generalization beyond the training domain. Such hybrid modeling would address concerns that purely data-driven models may underperform when service conditions differ significantly from the dataset. Field validation is particularly essential because real pipelines include weld zones and residual stresses, and weld integrity is a key pipeline reliability component, as indicated in multi-scale mechanics and fabrication integrity work (Wilkowski et al., 2008). The results justify the conclusion that ML prediction of HIC in X80 is not only feasible but metallurgically defensible, provided the approach remains mechanism-informed and validated through expanded datasets and field-oriented testing.

6. Conclusion

This research confirms that hydrogen-induced cracking (HIC) susceptibility in X80 grade pipeline steels may be predicted effectively using combinations of machine learning and competent metallurgical and sour-environment parameters. The developed model was able to capture the

nonlinear and interaction-controlled nature of HIC in which the cracking severity is not decided by a single factor, but rather the combined effect of the hydrogen charging conditions, the internal steel heterogeneity. Compared with conventional screening approaches, the use of the machine learning framework offered more dependable prediction of the HIC behaviour, while the approach was stable during model tuning and validation. The best influencers were sour severity characteristics (H2S partial pressure and pH), the heterogeneity of segregation (segregation and banding index), the structure of trap of hydrogen (inclusion density and maximum size of inclusion) and the localized characteristics of brittleness (maximum hardness and MA fraction). The mechanistic sequence of HIC represented by these variables is hydrogen entry, diffusion & trapping, crack initiation, and crack linking via hardened microstructural pathing. Importantly, the explainability analysis increased the credibility of the model through linking the prediction results to metallurgical mechanisms and not the results in a black box. The proposed ML-based framework has created a practical tool for the improvement of X80 pipeline integrity through predictive classification of HIC risk, steel quality control and risk-based inspection planning in sour and/or hydrogen-transition service conditions.

7. Recommendations

• Control not only average cleanliness but also the maximum inclusion size and inclusion clustering (upper-tail control).
• Strengthen secondary metallurgy practices (desulfurization, inclusion modification) to minimize elongated/complex inclusions acting as hydrogen traps.
• Reduce centerline segregation through improved slab homogenization and optimized TMCP process windows.
• Modify rolling and cooling schedules to minimize microstructural band continuity, and set banding index limits for X80 intended for sour/hydrogen transition service.
• Control localized hardness peaks (not only mean hardness) by limiting hard MA islands

and sharp hardness gradients through phase distribution control.
• Integrate ML-based HIC risk scores into integrity management and inspection scheduling to prioritize high-risk pipeline segments.
• Apply targeted NDT and higher inspection frequency for sections predicted as Susceptible, particularly under high H_2S and low pH exposure.

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