Prediction of Completion Fluid Stability and Productivity Impact in Challenging Reservoir Environments Using Machine Learning Analysis

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Abstract

This study aims to develop and validate machine learning models to predict completion fluid stability and quantitatively assess its impact on well productivity in challenging reservoir environments. The study employed a quantitative, applied research design based on historical completion and production data from onshore oil and gas reservoirs in Iran. The dataset integrated reservoir properties, completion fluid physicochemical characteristics, operational parameters, and post-completion productivity indicators. After data preprocessing, feature engineering, and normalization, multiple supervised machine learning algorithms—including linear, kernel-based, and ensemble models—were trained and evaluated. Robust cross-validation and hyperparameter optimization strategies were applied to ensure model generalizability and prevent overfitting. Model interpretability was addressed through feature importance analysis and sensitivity evaluation. Inferential results indicated that nonlinear ensemble models significantly outperformed linear approaches in predicting completion fluid stability, achieving high explanatory power and low prediction error. Reservoir temperature and formation water salinity emerged as the most influential predictors, followed by fluid thermal stability limits and filtration loss characteristics. Predicted stability classes exhibited statistically meaningful differences in productivity outcomes, with high-stability completions associated with substantially higher normalized productivity indices and initial production rates. The relationship between predicted stability and productivity was nonlinear, revealing a threshold beyond which incremental stability improvements yielded diminishing productivity gains. The findings confirm that machine learning provides a robust and interpretable framework for predicting completion fluid stability and its productivity implications under complex reservoir conditions. By linking stability predictions to measurable production outcomes, the proposed approach offers a practical decision-support tool for optimizing completion fluid design, reducing formation damage risk, and enhancing economic performance in challenging reservoirs.

Keywords: *Completion fluid stability; machine learning; well productivity; reservoir engineering; formation damage; data-driven modeling*

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1. Introduction

The increasing technical complexity of hydrocarbon reservoirs and the persistent drive toward cost-efficient and sustainable production have significantly intensified the need for advanced decision-support tools in well completion engineering. Completion fluids play a critical role in protecting reservoir integrity, ensuring wellbore stability, minimizing formation damage, and ultimately sustaining well productivity, particularly in reservoirs characterized by high temperature, high pressure, complex mineralogy, and chemically aggressive formation waters. In such challenging environments, even minor instability in completion fluid systems can trigger severe productivity impairment through mechanisms such as fines migration, clay swelling, emulsion blockage, and thermal or chemical degradation. Conventional empirical and physics-based approaches, while valuable, often struggle to fully capture the nonlinear, multiscale interactions among reservoir properties, fluid chemistry, and operational parameters, thereby motivating the integration of data-driven and machine learning-based analytical frameworks [1, 2].

Recent advances in machine learning have demonstrated substantial potential in addressing complex prediction problems across petroleum engineering disciplines, including reservoir characterization, enhanced oil recovery screening, fluid–rock interaction modeling, and operational optimization. Unlike traditional regression-based models, machine learning algorithms can learn intricate nonlinear patterns from high-dimensional datasets, making them particularly suitable for predicting performance metrics that are influenced by coupled thermal, chemical, and mechanical processes. This capability has been effectively demonstrated in studies related to interfacial tension prediction, foam stability, skin factor estimation, pore pressure forecasting, and enhanced oil recovery efficiency, all of which share conceptual similarities with the prediction of completion fluid stability and productivity impact [3-7].

Within the broader context of intelligent reservoir engineering, machine learning has increasingly been applied to model fluid behavior under extreme conditions. Research focusing on CO_2-based processes, such as minimum miscibility pressure prediction, foam half-life estimation, and solubility modeling in brine systems, highlights the effectiveness of data-driven approaches in capturing thermodynamic and physicochemical complexities that are otherwise difficult to parameterize explicitly [8-11]. These studies underscore a critical insight relevant to completion engineering: fluid performance is rarely governed by a single dominant variable, but rather by the collective influence of reservoir temperature, pressure, salinity, mineralogy, and fluid formulation characteristics. Consequently, predictive frameworks that can integrate these heterogeneous inputs are essential for reliable performance forecasting.

The application of machine learning in enhanced oil recovery and reservoir management has further reinforced the importance of predictive analytics in optimizing fluid-based interventions. Data-driven screening and optimization of EOR techniques, waterflooding performance estimation, and carbon sequestration efficiency assessment have all benefited from intelligent models capable of learning from historical field data [12-15]. These advancements provide a methodological foundation for extending machine learning applications to completion fluid systems, where similar challenges related to data heterogeneity, nonlinear interactions, and operational uncertainty prevail.

Despite these developments, the specific problem of predicting completion fluid stability and its direct impact on well productivity remains relatively underexplored in the literature. Existing completion fluid design practices largely rely on laboratory testing, empirical correlations, and expert judgment, which, although valuable, may not fully represent field-scale variability or account for complex reservoir–fluid interactions under dynamic operational conditions. Laboratory-derived stability indicators, such as thermal tolerance, filtration loss, and rheological consistency, do not always translate directly into field performance, particularly in reservoirs with strong geochemical reactivity or heterogeneous flow regimes. This gap between laboratory assessment and field outcome highlights the need for predictive models that explicitly link fluid stability metrics to actual productivity responses.

Parallel research in adjacent domains illustrates how machine learning can bridge similar gaps. For instance, intelligent models have been successfully employed to predict skin factor evolution, matrix acidizing effectiveness, and pressure responses in complex wellbore systems, providing actionable insights for operational optimization [16-18]. These applications demonstrate that machine learning can move beyond mere prediction toward enhanced interpretability and decision support, especially when combined with feature importance analysis and sensitivity evaluation. Such capabilities are particularly relevant for completion fluid optimization, where understanding the relative contribution of reservoir and fluid parameters is as important as achieving high predictive accuracy.

The relevance of machine learning-driven prediction is further amplified in regions such as Iran, where reservoirs often exhibit extreme thermal conditions, high salinity formation waters, and complex lithological compositions. These characteristics impose stringent requirements on completion fluid stability and increase the economic risk associated with fluid-induced formation damage. At the same time, the availability of extensive historical operational and laboratory data in mature Iranian fields creates a favorable environment for data-driven modeling. Leveraging these datasets through advanced analytics aligns with broader trends toward digital transformation and intelligent field development in the oil and gas industry [19-21].

Beyond petroleum engineering, machine learning methodologies have also demonstrated cross-disciplinary robustness in modeling complex physical and environmental systems, such as sediment mechanical response, water quality monitoring, and resource management under uncertainty. These applications reinforce the generalizability and adaptability of intelligent modeling frameworks when dealing with nonlinear, multivariate systems [22-24]. Such methodological maturity supports the argument that similar approaches can be reliably adapted to predict completion fluid behavior and its productivity implications.

Recent advances in deep learning and hybrid physics-informed models further enhance the prospects of accurate prediction in reservoir-related applications. Studies on phase equilibrium acceleration, history matching, and intelligent bit selection illustrate how advanced architectures can improve both computational efficiency and predictive fidelity [25-27]. These innovations suggest that machine learning models can effectively complement traditional engineering knowledge, particularly in scenarios where full-physics simulation is computationally prohibitive or data-intensive.

In parallel, growing interest in feature interpretability and model transparency has addressed one of the long-standing concerns associated with machine learning adoption in engineering practice. Feature importance analysis, sensitivity studies, and explainable AI techniques enable engineers to extract physical insight from data-driven models, thereby increasing trust and facilitating integration into operational workflows. This aspect is particularly critical for completion engineering decisions, which often involve high financial stakes and operational risk [28-30].

Collectively, the reviewed literature indicates a clear trajectory toward intelligent, data-driven prediction of fluid behavior and reservoir performance, yet also reveals a specific research gap in the integrated prediction of completion fluid stability and its productivity impact under challenging reservoir conditions. Addressing this gap requires a comprehensive analytical framework that combines diverse reservoir, fluid, and operational variables within robust machine learning models and evaluates their predictive and explanatory capabilities using real field data.

Accordingly, the aim of this study is to develop and validate machine learning models for predicting completion fluid stability and quantifying its impact on well productivity in challenging Iranian reservoir environments using integrated operational and laboratory datasets.

2. Methodology

The present study adopted an applied, quantitative, and predictive research design aimed at modeling completion fluid stability and its productivity implications under challenging reservoir conditions using machine learning techniques. The study context was upstream oil and gas operations in Iran, where heterogeneous lithology, high-temperature–high-pressure (HTHP) conditions, salinity variability, and formation sensitivity pose persistent challenges to completion fluid performance. The research was conducted using an ex post facto design based on historical operational data, as direct experimental manipulation of reservoir and completion conditions was neither feasible nor ethically appropriate. The statistical population comprised oil and gas wells completed in onshore Iranian reservoirs over a defined multi-year operational window, selected to ensure sufficient variability in reservoir characteristics and completion practices.

Sampling was performed using a purposive and criterion-based approach to ensure that only wells with complete, reliable, and traceable datasets were included. Inclusion criteria required the availability of comprehensive completion fluid formulation data, reservoir thermodynamic properties, operational parameters during completion, and post-completion productivity indicators. Wells with incomplete logs, missing laboratory fluid stability tests, or ambiguous production records were excluded to prevent model bias and data leakage. The final analytical dataset was constructed at the well–completion stage level, allowing multiple completion events per well where applicable. This approach enabled the capture of operational heterogeneity across different fields and geological settings while maintaining internal consistency in data granularity. The sample size was determined based on machine learning requirements for model generalization rather than classical statistical power, with an emphasis on maximizing feature diversity and minimizing sparsity.

Data were collected through the integration of multiple operational, laboratory, and production data sources routinely used in Iranian oilfield development projects. Completion fluid properties were obtained from standardized laboratory reports, including physicochemical parameters such as density, rheology indices, thermal stability thresholds, filtration loss, emulsion tendency, and compatibility indicators with formation fluids and rock samples. Reservoir characteristics were extracted from petrophysical logs, core analysis reports, and reservoir engineering databases, covering parameters such as formation temperature and pressure, mineralogical composition, porosity, permeability, water salinity, and clay content indices. Operational data related to completion practices, including pumping rates, fluid volumes, contact time, and wellbore configuration, were collected from daily drilling and completion reports.

Productivity-related outcomes were measured using early-time production indicators, including initial production rates, drawdown efficiency, and normalized productivity indices adjusted for reservoir pressure and choke conditions. To ensure data integrity, all datasets were cross-validated against field-level supervisory records, and inconsistencies were resolved through expert review by completion and reservoir engineers. Prior to analysis, the collected data underwent preprocessing procedures, including unit harmonization, missing value treatment using statistically justified imputation methods, and outlier detection based on both statistical thresholds and engineering plausibility. Feature scaling and normalization were applied where required to ensure compatibility across different machine learning algorithms and to prevent dominance of high-magnitude variables.

Data analysis was conducted using a machine learning workflow designed to predict completion fluid stability outcomes and quantify their impact on post-completion productivity. The analytical process began with exploratory data analysis to assess variable distributions, intercorrelations, and potential multicollinearity among predictors. Feature engineering techniques were employed to derive composite indicators representing fluid–reservoir interaction intensity, thermal–chemical stress indices, and operational complexity scores. These engineered features were developed in close consultation with domain experts to ensure physical interpretability and operational relevance.

Multiple supervised machine learning algorithms were implemented, including tree-based ensemble models, kernel-based learners, and regularized regression approaches, to capture both linear and nonlinear relationships between input features and target variables. Completion fluid stability was modeled as both a continuous outcome, reflecting degradation or performance loss metrics, and a categorical outcome representing stable versus unstable operational states. Model training and evaluation followed a robust validation strategy using stratified data partitioning to preserve the distribution of key reservoir conditions across training and testing subsets. Hyperparameter optimization was conducted using grid and randomized search techniques combined with cross-validation to prevent overfitting and enhance generalizability.

Model performance was evaluated using a combination of error-based and classification metrics, selected in accordance with the nature of each prediction task. In addition to predictive accuracy, model interpretability was addressed through post hoc explanation techniques, enabling the identification of the most influential completion fluid and reservoir parameters driving stability and productivity outcomes. Sensitivity analyses were performed to assess the robustness of model predictions under varying operational scenarios. All analyses were conducted using validated scientific computing and machine learning libraries within a reproducible computational environment, ensuring transparency, replicability, and applicability of the results for decision support in Iranian reservoir completion operations.

3. Findings and Results

The findings section presents the empirical outcomes of the machine learning analysis conducted to predict completion fluid stability and its impact on well productivity under challenging reservoir conditions. The results are organized to progressively describe the dataset characteristics, model performance, key predictive variables, and the quantified relationship between fluid stability and productivity outcomes. Table 1 provides a comprehensive descriptive summary of the study variables, establishing the empirical context for subsequent predictive analyses.

Table 1. Descriptive statistics of reservoir, completion fluid, and productivity variables

Variable	Mean	Standard Deviation	Minimum	Maximum
Reservoir temperature (°C)	128.4	18.7	92.0	176.0
Reservoir pressure (MPa)	41.6	7.9	26.5	59.8
Formation water salinity (ppm)	186,500	42,300	98,000	265,000
Clay content index (%)	21.3	8.6	6.5	39.8
Completion fluid density (g/cm³)	1.21	0.09	1.05	1.42
Plastic viscosity (cP)	38.7	11.4	19.2	74.5
Fluid thermal stability limit (°C)	152.6	14.1	118.0	186.0
Filtration loss (mL/30 min)	7.9	3.1	2.4	16.8

Stability degradation index	0.27	0.15	0.04	0.68
Initial production rate (bbl/day)	2,940	1,120	740	6,180
Normalized productivity index	1.00	0.34	0.42	1.96

As shown in Table 1, the dataset reflects substantial heterogeneity in reservoir conditions and completion fluid properties, confirming the presence of operationally challenging environments. Reservoir temperatures and salinity levels indicate predominantly high-temperature and high-salinity systems, which are known to exacerbate chemical instability in completion fluids. The variability observed in the stability degradation index and productivity indicators suggests that fluid performance outcomes were not uniform across wells, thereby justifying the application of machine learning techniques to capture complex nonlinear relationships.

Table 2. Predictive performance of machine learning models for completion fluid stability

Model	RMSE	MAE	R^2
Regularized linear regression	0.112	0.089	0.62
Support vector regression	0.086	0.067	0.74
Random forest regression	0.063	0.049	0.86
Gradient boosting model	0.058	0.045	0.89

Table 2 demonstrates that nonlinear ensemble-based models substantially outperformed linear approaches in predicting completion fluid stability. The gradient boosting model achieved the highest explanatory power and the lowest prediction error, indicating its superior capability in modeling complex interactions between reservoir conditions, fluid properties, and operational parameters. These findings confirm that completion fluid stability is governed by nonlinear mechanisms that cannot be adequately captured using traditional linear predictive techniques.

Table 3. Relative importance of key predictors in the optimal stability prediction model

Predictor variable	Relative importance (%)
Reservoir temperature	24.6
Formation water salinity	19.8
Fluid thermal stability limit	17.4
Clay content index	14.2
Filtration loss	9.6
Plastic viscosity	7.3
Completion pumping rate	4.1
Fluid density	3.0

According to Table 3, reservoir temperature emerged as the most influential predictor of completion fluid stability, followed by formation water salinity and the intrinsic thermal resistance of the fluid formulation. The prominence of clay content and filtration loss highlights the critical role of fluid–rock interactions in stability degradation. Operational variables exhibited comparatively lower importance, indicating that while execution parameters matter, intrinsic reservoir and fluid characteristics primarily govern stability outcomes in challenging environments.

Table 4. Impact of predicted completion fluid stability on productivity outcomes

Stability class	Mean initial production (bbl/day)	Mean normalized productivity index
High stability	3,520	1.24
Moderate stability	2,880	0.98
Low stability	1,940	0.71

Table 4 reveals a clear and systematic relationship between predicted completion fluid stability and well productivity. Wells classified within the high-stability category exhibited substantially higher initial production rates and productivity indices compared with those experiencing moderate or low stability. The magnitude of the productivity decline associated with low stability underscores the economic significance of accurate fluid design and predictive assessment prior to completion operations.

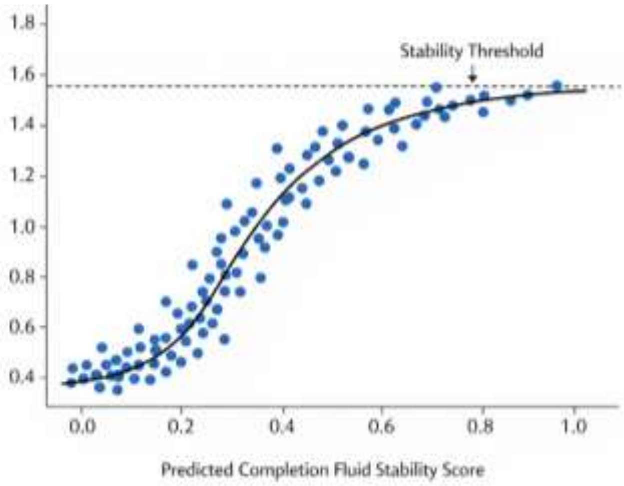

Figure 1. Nonlinear relationship between predicted completion fluid stability score and normalized productivity index

The results illustrated in Figure 1 indicate a pronounced nonlinear association between predicted fluid stability scores and productivity performance. At lower stability levels, small improvements in stability correspond to disproportionately large gains in productivity, whereas at higher stability ranges, productivity gains tend to plateau. This pattern suggests the existence of a practical stability threshold beyond which further chemical optimization yields diminishing returns, providing a valuable decision-support insight for completion fluid design and cost optimization in complex reservoir environments.

4. Discussion and Conclusion

The findings of this study demonstrate that machine learning models can effectively predict completion fluid stability and meaningfully quantify its impact on well productivity in challenging reservoir environments. The superior performance of ensemble-based and nonlinear algorithms observed in the results aligns with the intrinsic complexity of completion fluid behavior, which is governed by coupled thermal, chemical, and rock–fluid interaction mechanisms. The strong predictive accuracy achieved by gradient boosting–type models confirms that completion fluid stability cannot be adequately explained through linear assumptions alone, a conclusion that is consistent with broader petroleum engineering research emphasizing the nonlinear nature of reservoir and fluid systems [12, 15, 22]. The ability of machine learning to integrate heterogeneous inputs and extract latent patterns provides a compelling explanation for the observed improvements over traditional regression-based approaches.

One of the most significant findings of this study is the dominant influence of reservoir temperature and formation water salinity on completion fluid stability. This result is fully consistent with prior research demonstrating that elevated temperature accelerates chemical degradation, polymer breakdown, and emulsion instability, while high salinity exacerbates incompatibility reactions and reduces the effectiveness of stabilizing additives. Similar conclusions have been reported in machine learning-based studies of foam stability, interfacial tension, and solubility behavior under extreme reservoir conditions, where temperature and ionic strength consistently emerge as primary drivers of fluid performance [4, 10, 11]. The present findings extend these insights specifically to completion fluid systems, reinforcing the need for predictive tools that explicitly account for these dominant reservoir stressors.

The strong contribution of intrinsic fluid properties, particularly thermal stability limits and filtration loss characteristics, further validates the physical relevance of the developed models. Completion fluids designed with higher thermal tolerance exhibited significantly lower predicted degradation indices, which translated into improved productivity outcomes. This relationship supports the argument that laboratory-derived stability indicators retain predictive value at the field scale when appropriately contextualized within a data-driven framework. Comparable observations have been reported in studies focusing on intelligent modeling of fluid behavior and EOR chemical performance, where machine learning successfully bridged the gap between laboratory measurements and field-scale responses [31-33]. The present study confirms that such transferability is also achievable for completion fluid stability when sufficient operational and reservoir data are incorporated.

The importance assigned to clay content and filtration loss in the predictive models underscores the critical role of fluid–rock interactions in governing post-completion performance. High clay content formations are particularly susceptible to fines migration, swelling, and pore throat blockage when exposed to unstable or incompatible completion fluids. The model's sensitivity to these variables is consistent with prior work on skin factor evolution, formation damage prediction, and matrix treatment effectiveness, where mineralogical composition has been identified as a key determinant of near-wellbore performance [5, 16, 17]. By quantitatively capturing these effects, the developed models provide a more nuanced understanding of how completion fluid stability translates into measurable productivity outcomes.

The observed nonlinear relationship between predicted fluid stability and normalized productivity index provides important practical insight. The results indicate that productivity gains associated with improving fluid stability are most pronounced at low-to-moderate stability levels, after which marginal benefits diminish. This finding is consistent with economic and operational observations reported in intelligent optimization studies, where diminishing returns are frequently observed once a critical performance threshold is exceeded [8, 9, 13]. From an engineering perspective, this implies that overly conservative or excessively complex fluid formulations may not yield proportional productivity benefits, highlighting the value of predictive models for identifying optimal stability targets rather than maximal ones.

The classification-based analysis linking stability classes to productivity outcomes further strengthens the causal interpretation of the results. Wells predicted to experience high completion fluid stability consistently exhibited higher initial production rates and productivity indices than those classified as moderate or low stability. This systematic trend aligns with established understanding of formation damage mechanisms and is supported by machine learning studies that have linked intelligent predictions of skin factor, pressure response, and fluid performance to actual production behavior [18, 26, 29]. The present study contributes novel empirical evidence by explicitly quantifying this relationship for completion fluids in real field conditions.

The robustness of the developed models is further supported by their consistency with findings from adjacent domains within petroleum engineering. Intelligent prediction of pore pressure, permeability, porosity, and interfacial properties has repeatedly demonstrated that data-driven models can outperform traditional correlations, particularly in heterogeneous and data-rich environments [6, 7, 28]. The successful application of similar methodologies to completion fluid stability suggests that such models are not only technically sound but also transferable across multiple subsurface engineering problems.

The Iranian reservoir context of this study adds additional relevance to the findings. Many Iranian fields are characterized by high-temperature carbonate formations, saline formation waters, and complex completion histories, making them ideal candidates for data-driven optimization. The alignment of the results with prior regional and international studies on intelligent reservoir monitoring and sustainable production strategies reinforces the applicability of machine learning as a strategic tool for modern field development [1, 2, 19]. By leveraging historical operational data, the study demonstrates how advanced analytics can support more resilient and economically efficient completion decisions.

The findings also resonate with emerging trends toward physics-informed and hybrid machine learning approaches. Although the models developed in this study were primarily data-driven, the clear physical interpretability of key predictors suggests strong potential for integration with physics-based constraints in future work. Similar hybrid approaches have already shown promise in compositional simulation acceleration, history matching, and mechanical response prediction, indicating a broader methodological convergence within the field [22, 25, 27]. Such integration could further enhance predictive reliability while maintaining computational efficiency.

Finally, the study contributes to the growing body of evidence supporting explainable and decision-oriented machine learning in petroleum engineering. By identifying the relative importance of reservoir, fluid, and operational parameters, the models provide actionable insight rather than black-box predictions. This aligns with recent calls for interpretable artificial intelligence in subsurface applications, particularly in high-risk operational contexts such as completion design and stimulation planning [23, 30, 34]. The demonstrated ability to link predicted stability to tangible productivity outcomes represents a meaningful step toward operationalizing machine learning for completion engineering decision support.

Despite its contributions, this study is subject to several limitations. The analysis relied on historical operational and laboratory data, which may contain inherent measurement uncertainty and reporting inconsistencies that could influence model performance. Additionally, the dataset, while diverse, was limited to specific reservoir types and completion practices, potentially constraining the generalizability of the findings to markedly different geological or operational settings. The study also focused on early-time productivity indicators, and longer-term production behavior was not explicitly modeled.

Future research could extend the present framework by incorporating time-dependent production data to evaluate the long-term effects of completion fluid stability on reservoir performance. Expanding the dataset to include offshore fields, unconventional reservoirs, or alternative completion technologies would further enhance model generalizability. Moreover, integrating physics-informed constraints or hybrid modeling approaches could improve interpretability and robustness under data-scarce conditions.

From a practical standpoint, the results suggest that operators should prioritize predictive assessment of completion fluid stability using data-driven tools during the design phase, particularly in high-temperature and high-salinity reservoirs. Emphasis should be placed on achieving optimal rather than maximal stability to balance chemical cost and productivity gains. Incorporating machine learning-based decision support into routine completion planning can enhance risk mitigation, improve productivity outcomes, and support more sustainable reservoir development strategies.

Authors' Contributions

Authors equally contributed to this article.

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Declaration of Interest

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Ethical Considerations

All procedures performed in this study were under the ethical standards.

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