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RESEARCH ARTICLE

WaveInsight: A Source-Independent Full Waveform Inversion Application for Seismic Modeling

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Abstract

Full Waveform Inversion (FWI) is a key method in seismic exploration due to its ability to generate high-resolution subsurface velocity models. However, its success is highly dependent on the accuracy of the source wavelet, an incorrect wavelet estimation can lead to unstable inversion results. To overcome this limitation, Source-Independent FWI (SI-FWI) has been developed, which eliminates the need for precise source wavelet information. This study introduces WaveInsight, an application that efficiently implements SI-FWI using the Julia programming language, with Python integration via Devito for wave simulation. The application features a Streamlit-based graphical user interface, enabling users to perform a complete FWI workflow, including data preparation, initial model generation, and inversion. Experiments on synthetic Overthrust data compare three objective functions: Student-t, Mean Squared Error (MSE), and SI-FWI. The results show that SI-FWI outperforms conventional approaches under wavelet uncertainty, Student-t is more robust to noise, while MSE performs well with clean data. Thus, WaveInsight demonstrates its dual role as both an educational platform and a promising tool for advancing geophysical research and industrial applications.

Keywords: Full Waveform Inversion, Source-Independent FWI, Seismic Modeling

1. Introduction

Seismic methods are a primary technique in geophysical exploration, aimed at mapping subsurface structures and physical properties. One of the most rapidly advancing approaches in the past decade is Full Waveform Inversion (FWI), which leverages the entire seismic waveform to produce high-resolution subsurface velocity models (Berkhout, 2012; Fichtner et al., 2013; Geng et al., 2011; Tarantola, 1984; Virieux and Operto, 2009; Yao et al., 2020). The key advantage of FWI lies in its ability to capture geological details more accurately than conventional inversion methods, making it highly valuable for hydrocarbon, geothermal, and other energy resource exploration (Brittan and Jones, 2019; Shen et al., 2018; Tromp, 2020).

However, the success of FWI implementation strongly depends on multiple factors, including the initial model, broadband data, and the availability of accurate source wavelet information (Jin et al., 2024; Sun et al., 2023; Winardhi et al., 2025, 2024a, 2024b). Among these, wavelet estimation is particularly critical: inaccuracies in the source wavelet can cause inversion instabilities, introduce artifacts, and even lead to failure in reconstructing subsurface structures (Qi et al., 2023; Zhang et al., 2016). Such issues are frequently encountered in field data, especially in onshore seismic acquisition under complex conditions and variable data quality.

To address these limitations, (Zhang et al., 2016) proposed the Source-Independent Full Waveform Inversion (SI-FWI) method, which removes the dependency on precise source wavelet information. This approach allows inversion to be performed more robustly under real data conditions. A more recent study by (Winardhi et al., 2024a) demonstrated that SI-FWI can be effectively applied to onshore seismic data in Indonesia, yielding reliable subsurface models even when the source wavelet is not accurately known.

The growing adoption of SI-FWI has increased the need for practical, efficient, and user-friendly computational platforms to support both research and education. Julia provides exceptional performance for large-scale numerical computing and PDE-based inversion (Jin et al., 2024; Ruthotto et al., 2017), while Python offers a mature ecosystem for data processing, signal analysis, and integration with geophysical workflows (Hoving et al., 2013; Krell et al., 2013; Krischer et al., 2015). The widespread use of Python in recent geoscience studies ranging from seismic signal processing with ObsPy (Khusnani et al., 2024), HVSR and microtremor interpretation supported by Python-based tools (Yatini et al., 2023), InSAR deformation analysis using the LiCSBAS Python package (Muhammad Razzaaq Al Ghiffari et al., 2024) , to deep learning applications for digital rock characterization (Akmal et al., 2023), demonstrates the relevance and reliability of open-source computational geophysics in real-world research.

At the application level, Streamlit provides an accessible and interactive web-based interface for scientific visualization and rapid prototyping (Jaelani and Pangestu, 2023)), making it highly suitable for educational and research environments. By integrating these complementary technologies, the WaveInsight platform was designed as a GUI-based environment that unifies Python-powered wave simulation (Devito), Julia-based inversion engines (JUDI), and interactive user interfaces through Streamlit. This combination leverages the computational strengths of Julia and the ecosystem richness of Python, supported by proven real-world implementations in recent geoscience literature, to provide a modern, efficient, and accessible framework for SI-FWI experimentation and learning.

Therefore, this study introduces WaveInsight as an application that implements SI-FWI, designed not only for research purposes but also as a valuable educational tool. The application enables users to perform the complete FWI workflow, from data preparation and initial model building to inversion in a simplified and efficient manner.

2. Theoretical Background

2.1 Full Waveform Inversion

Full Waveform Inversion (FWI) is a data-fitting technique that reconstructs subsurface parameters by minimizing the difference between observed and modeled seismic wavefields (Alkhalifah and Choi, 2013; Huang et al., 2021). The conventional FWI problem can be expressed as the optimization (Virieux and Operto, 2009):

$$\Phi_{SI}(\boldsymbol{m}) = \frac{1}{2}\sum_{s,r}\left\|d_{obs}(s,r,t) - d_{syn}(s,r,t;m)\right\|^2 \quad (1)$$

where $\boldsymbol{m}$ denotes the model parameters, d_{obs} the observed data, and d_{syn} the synthetic data simulated for source s and receiver r.

A key limitation of this formulation is its strong dependence on the accuracy of the source wavelet (Choi and Alkhalifah, 2011; Qi et al., 2023; Zhang et al., 2016). In practice, inaccuracies in wavelet estimation can introduce phase and amplitude mismatches, leading to cycle-skipping, artifacts, and even inversion failure (Pladys et al., 2021). This dependency is particularly problematic in land seismic acquisition, where the source signature is often poorly known.

2.2 Source Independent Full Waveform Inversion

In conventional FWI, the objective function is typically defined as the least-squares difference between observed and modeled data, making it highly sensitive to inaccuracies in the source wavelet (Qi et al., 2023; Sigalingging et al., 2021; Yang and Engquist, 2018; Zhang et al., 2016). (Zhang et al., 2016) introduced a convolutional or normalized cross-correlation based misfit function, which removes the explicit dependence on the source wavelet by comparing the phase and relative amplitude of the recorded and simulated signals rather than their absolute values. This formulation ensures that inversion remains stable even when the exact source signature is uncertain or unknown.

The Source independent objective function consists of the convolution of the observed wavefield with a reference trace chosen from the modeled seismogram, minus the convolution of the modeled wavefield with a reference trace selected from the observed seismogram. We implemented the formula of the time domain source independent FWI defined by (Zhang et al., 2016) the objective function defined by:

$$\chi(m) = \frac{1}{2}\left\|d^{syn} * (Wd_{ref}^{obs}) - d^{obs} * (d_{ref}^{syn})\right\|_2^2 \quad (2)$$

The back-propagated source of the adjoint wave equation based on the objective function above is defined by:

$$r' = (Wd_{ref}^{obs}) \otimes \mathrm{r} \quad (3)$$

Where $r = d^{syn} * (Wd_{ref}^{obs}) - d^{obs} * (Wd_{ref}^{syn})$, * is stand for convolution operator, $\chi(m)$ is objective function, d^{syn} is synthetic seismic data by forward simulation, d^{obs} is observation data, d_{ref}^{syn}, d_{ref}^{obs} are synthetic and observation reference traces, these defined by the mean stack of n traces, which is picked around the source location, we choose 5 to 10 traces in this study, W is a time window to avoid noise from the effect of a convolutional operator.

The time window can suppress the noise induced by the convolution and cross-correlation operations almost without losing the information of effective signals, improving the resolution of the inversion results, and accelerating the convergence rate. The inversion algorithm is based on spectral projection gradient.

3. Implementation in WaveInsight

The development of WaveInsight integrates recent advances in numerical simulation, inversion frameworks, and modern application interfaces to provide an accessible platform for Source-Independent Full Waveform Inversion (SI-FWI). The implementation combines Devito (Python) for wavefield simulation, JUDI (Julia) for inversion optimization, and Streamlit (Python) for the graphical user interface (GUI). This section describes the system requirements, software architecture, and main workflow of the application.

3.1 System Requirements and Software Environment

WaveInsight has been tested on Linux Ubuntu 22.04 LTS, deployed both locally and within the Windows Subsystem for Linux (WSL) on Windows 11. The system relies on the following components:

a) **Wave Propagation Simulation**: Implemented using the Devito library in Python 3 (Luporini et al., 2020). Devito employs symbolic definitions of partial differential equations (PDEs) and just-in-time (JIT) compilation to generate efficient wave solvers.

b) **Inversion Framework**: Implemented using JUDI (Julia Devito Inversion framework), which enables large-scale symbolic inversion and provides efficient optimization routines (Witte et al., 2019).

c) **Graphical User Interface**: Developed with Streamlit in Python, enabling interactive workflows for data preparation, model building, and inversion.

The installation procedure requires Python 3.x, the GCC compiler for Devito backends, Julia (v1.10.x), and the WaveInsight source code hosted on GitHub. Once installed, the application is executed via Streamlit run main.py, launching an interactive GUI accessible through a web browser.

3.2 Software Architecture

The architecture of WaveInsight consists of three main modules (Fig.1):

1. **Prepare Shot Data**: Handles seismic gather input, geometry quality control, and amplitude inspection. Frequency-domain filters (e.g., bandpass) can be applied to remove unwanted noise and prepare shot records for inversion.
2. **Prepare Model**: Allows users to either generate smoothed velocity models automatically or upload externally derived models. Geometry consistency checks ensure that model domains match the seismic acquisition parameters.
3. **Imaging (Inversion)**: Executes the FWI process using different objective functions, including Student-t, Mean

Squared Error (MSE), and SI-FWI. The inversion routine employs Spectral Projected Gradient (SPG) optimization with velocity constraints and user-defined iteration limits.

This modular design provides a clear separation between preprocessing, model initialization, and inversion, while maintaining flexibility for research and educational purposes.

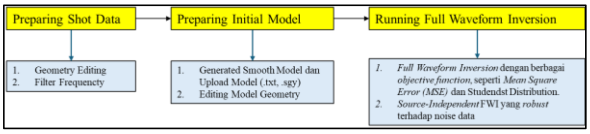

Fig.1. Main functional modules of WaveInsight: Prepare Shot Data, Prepare Model, and Full Waveform Inversion.

3.2 Workflow

The application workflow mirrors standard FWI procedures but is streamlined through the GUI:

1. **Data Preparation**: Shot gathers are uploaded and inspected for geometry consistency. Users can edit headers, apply filters, and save preprocessed datasets in SEG-Y format. The menu shown in Fig. 2

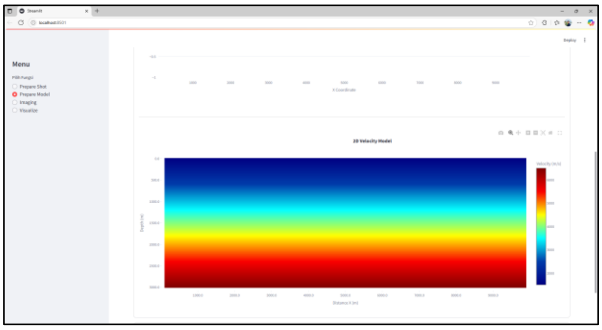

Fig. 2 The menu editor for Preparing Shot data. Include the menu loading data.

2. **Model Preparation**: Initial models are generated or imported. Smooth Gaussian models are commonly used as starting models to avoid overfitting early iterations. The menu is shown Fig. 3

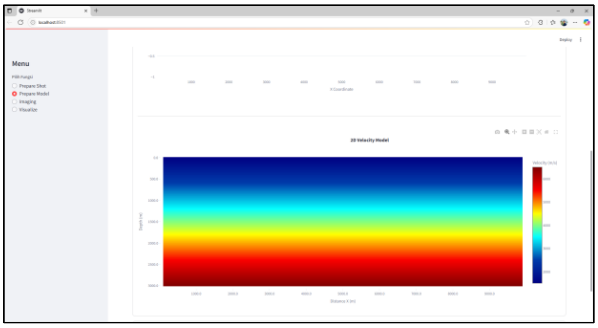

Fig. 3 The menu for Preparing Initial Model.

3. **Inversion**:
   a) Users select objective functions (Student-t, MSE, or SI-FWI).
   b) Wavelet parameters are defined, with the option to deliberately mismatch the inversion wavelet to test robustness.
   c) In SI-FWI mode, additional parameters (reference shot selection, stacking traces, and time windows) are specified.
   d) The inversion is executed iteratively, with intermediate results visualized in real time. The inversion menu is shown in Fig. 4

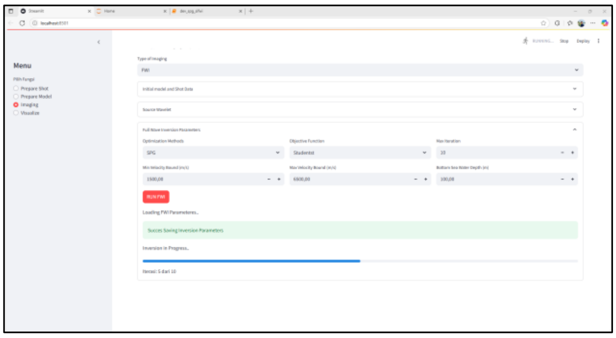

Fig. 4 The menu for running imaging (Full Waveform Inversion)

4. Experimental

4.1 Dataset and Experimental Setup

The performance of WaveInsight was evaluated using the synthetic Overthrust model (Luporini et al., 2020; Witte et al., 2019), shown in Fig. 5. The Overthrust model is a standard benchmark in seismic inversion research, characterized by complex velocity variations, making it suitable for testing algorithm robustness. The acquisition setup is summarized in Table 1.

Table 1. Acquisition parameters for the Overthrust dataset.

No	Parameter	Value
1	Type Wavelet	Ricker Zero-Phase
2	Dominant Frequency	8 Hz
3	Grid Spacing (x, z)	(25, 25) m
4	Grid Size (x, z)	(401, 121)
5	Number of Shots	16
6	Number of Receivers	197

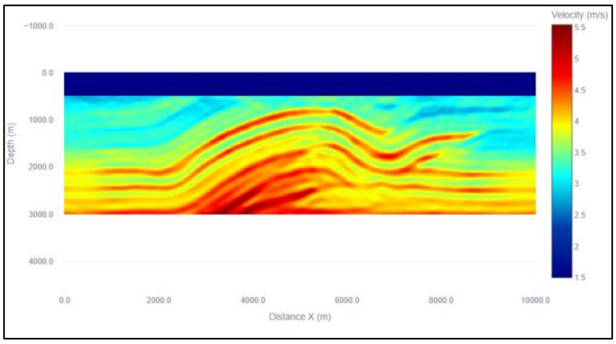

Fig. 5 True Overthrust velocity model used in the experiment.

4.2 Inversion Scenarios

Two inversion scenarios were designed to investigate the effect of wavelet uncertainty and to test both the robustness of the application and the inversion methods.

Scheme 1: Correct Wavelet

a) True source wavelet: Ricker, 8 Hz (identical to the modeling wavelet).
b) Initial model: smoothed Gaussian version of the true velocity model.
c) Objective functions: Student-t, Mean Squared Error (MSE), and Source-Independent FWI (SI-FWI).

d) Maximum iterations: 10.

Scheme 2: Incorrect Wavelet

a) Inversion wavelet: Ricker, 12 Hz (mismatched with data generation).
b) Initial model: smoothed Gaussian version of the true velocity model.
c) Objective functions: Student-t, MSE, and SI-FWI.
d) Maximum iterations: 15.

5. Result and Discussion

One of the principal advantages of WaveInsight is its ability to integrate advanced inversion algorithms within an intuitive graphical user interface (GUI). In contrast to conventional FWI workflows, which often require manual scripting and extensive knowledge of inversion codes, WaveInsight provides a streamlined environment through three dedicated modules: Prepare Shot Data, Prepare Model, and Full Waveform Inversion.

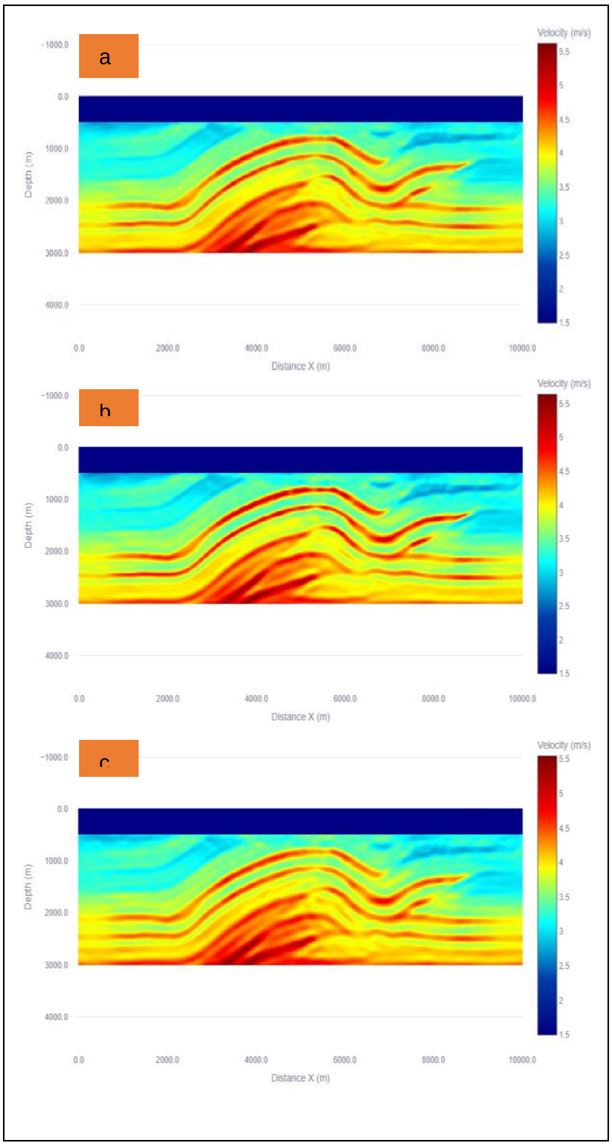

Fig. 6 Inversion results for Scheme 1 (correct wavelet, 8 Hz Ricker). (a) Student-t objective, (b) MSE objective, and (c) SI-FWI objective. All methods reconstruct the main subsurface structures, with SI-FWI showing the most stable convergence.

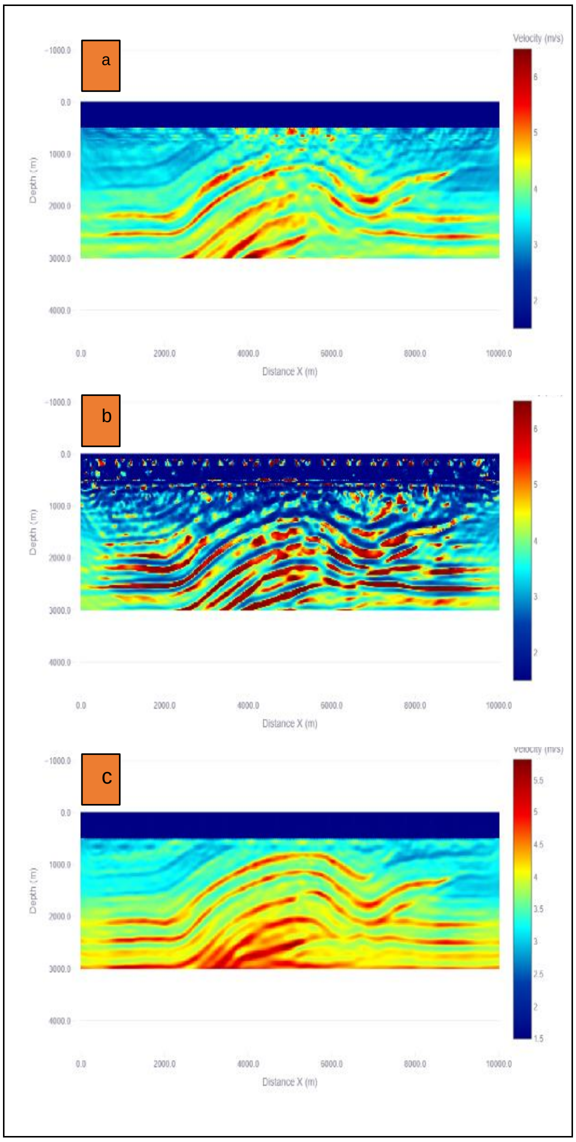

Fig. 7 Inversion results for Scheme 2 (incorrect wavelet, 12 Hz Ricker). (a) Student-t objective, (b) MSE objective, and (c) SI-FWI objective. SI-FWI demonstrates robustness to wavelet mismatch, while MSE produces significant artifacts.

The Shot Data Preparation module enables users to upload seismic gathers, conduct geometry quality control, and apply band-pass filtering, with the added benefit of direct visualization of frequency spectra. The Model Preparation module allows for the generation of smoothed initial velocity models or the import of externally derived models, while also offering geometry consistency checks to ensure alignment with acquisition parameters. Finally, the FWI Execution module supports interactive configuration of inversion parameters, objective function selection (Student-t, MSE, or SI-FWI), and real-time monitoring of inversion progress.

This modular GUI design substantially lowers the technical entry barrier for performing FWI. As a result, researchers and students are able to conduct full inversion workflows with greater efficiency, allowing their efforts to be directed toward data interpretation and analysis rather than low-level programming.

The performance of WaveInsight was assessed using the synthetic Overthrust dataset under two inversion scenarios designed to test sensitivity to source wavelet specification.

In Scheme 1 (Correct Wavelet, 8 Hz Ricker), the FWI result shows in Fig. 6, all three objective functions; Student-t, mean squared error (MSE), and source-independent FWI (SI-FWI), produced reliable subsurface reconstructions. Both SI-FWI and Student-t demonstrated stability comparable to the conventional least-squares misfit, thereby confirming that WaveInsight is capable of reproducing standard FWI performance under ideal conditions.

In Scheme 2 (Incorrect Wavelet, 12 Hz Ricker), the inversion problem became significantly more challenging. In this case, only SI-FWI yielded robust results, successfully recovering the primary geological features despite the mismatch between the assumed and true source wavelets. The Student-t objective function exhibited moderate robustness, producing acceptable but less accurate models, whereas the MSE approach generated severe artifacts, underscoring its vulnerability to wavelet uncertainty. The results are shown in Fig. 7 . This outcome illustrates the statistical robustness of the Student-t objective, the wavelet-independence of SI-FWI, and the phase sensitivity of MSE.

The inversion results for the Overthrust dataset are summarized in Table 2.

Table 2. The inversion results for the Overthrust dataset

Scheme	Objective Function	Result Summary
1 (Correct Wavelet)	Student-t	Reconstructed structures accurately; robust against moderate noise.
1 (Correct Wavelet)	MSE	Stable results under ideal conditions; good resolution.
1 (Correct Wavelet)	SI-FWI	Produced reliable results comparable or superior to other objectives.
2 (Incorrect Wavelet)	Student-t	Moderate reconstruction quality; some artifacts present.
2 (Incorrect Wavelet)	MSE	Strongly degraded results; severe artifacts due to wavelet mismatch.
2 (Incorrect Wavelet)	SI-FWI	Successfully reconstructed subsurface structure; robust to wavelet error.

6. Conclusion

This study introduced WaveInsight, a graphical application designed to implement both conventional Full Waveform Inversion (FWI) and Source-Independent FWI (SI-FWI) within a unified, user-friendly platform. By integrating advanced inversion algorithms with a streamlined graphical user interface (GUI), WaveInsight simplifies the otherwise complex workflow of seismic inversion. The three core modules are Prepare Shot Data, Prepare Model, and Full Waveform Inversion, enable users to perform geometry quality control, generate or import initial models, configure inversion parameters, and monitor results interactively. This design substantially lowers the technical barrier to conducting FWI, making the application accessible to both researchers and students.

Validation with the synthetic Overthrust dataset showed that WaveInsight reliably reproduces conventional FWI results under correct wavelet conditions, while SI-FWI demonstrates clear robustness when the source wavelet is uncertain. These results confirm the dual value of WaveInsight as both an educational platform and a research tool. With its accessibility and robustness, WaveInsight has the potential to accelerate adoption of SI-FWI in both academic and applied geophysical settings.

7. Acknowledgments

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8. Code and Data Availability

The WaveInsight source code and accompanying synthetic Overthrust dataset used in this study are openly available at: https://github.com/asidosaputra/waveinsight

This repository contains the full implementation, installation guide, and example workflows for reproducing the results presented in this paper.

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