



# Uncertainty-aware Neural Networks for Fuzzy Dark Matter Model Selection from $x_{\text{HI}}$ Measurements

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## Introduction

Many standard  $\Lambda$ CDM-consistent reionization models predict a relatively rapid reionization history, but recent James Webb Space Telescope (JWST) observations indicate a higher neutral hydrogen fraction ( $x_{\text{HI}}$ ) at  $z > 8$ . This tension motivates testing whether a modified dark-matter scenario can better reproduce the high-redshift reionization history implied by JWST.

Fuzzy dark matter (FDM) consists of ultralight axions whose quantum pressure suppresses sub-kiloparsec density fluctuations [1]. This naturally delays early low-mass halo collapse and postpones star formation, extending the reionization timeline.

JWST yields non-Gaussian posteriors, making point estimates inadequate. Since reionization is both spatial and temporal, we adopt a hybrid architecture to model both efficiently.

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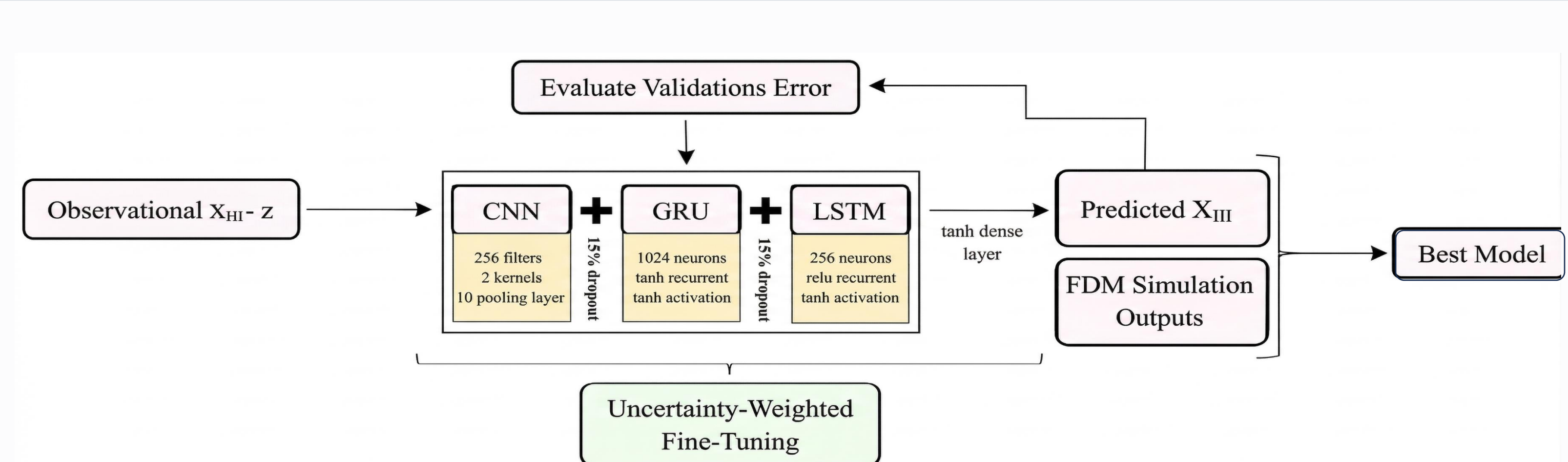
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## Method

### Four-step pipeline

- 1 We generated 21 cm histories using 21cmFirstCLASS [2] across a grid of  $m_{\text{FDM}} \in [10^{-24}, 10^{-21}]$  eV and  $f_{\text{FDM}} \in [0.02, 0.10]$
- 2 We used Bayesian No-U-Turn Sampler (NUTS) inference to build JWST-based probability distributions for  $x_{\text{HI}}$  and redshift.
- 3 We trained a CNN to extract spatial dependencies from the uncertainty maps, while GRU and LSTM layers captured the temporal redshift evolution.
- 4 We selected the FDM scenario that best matches the machine-learned observational trend.

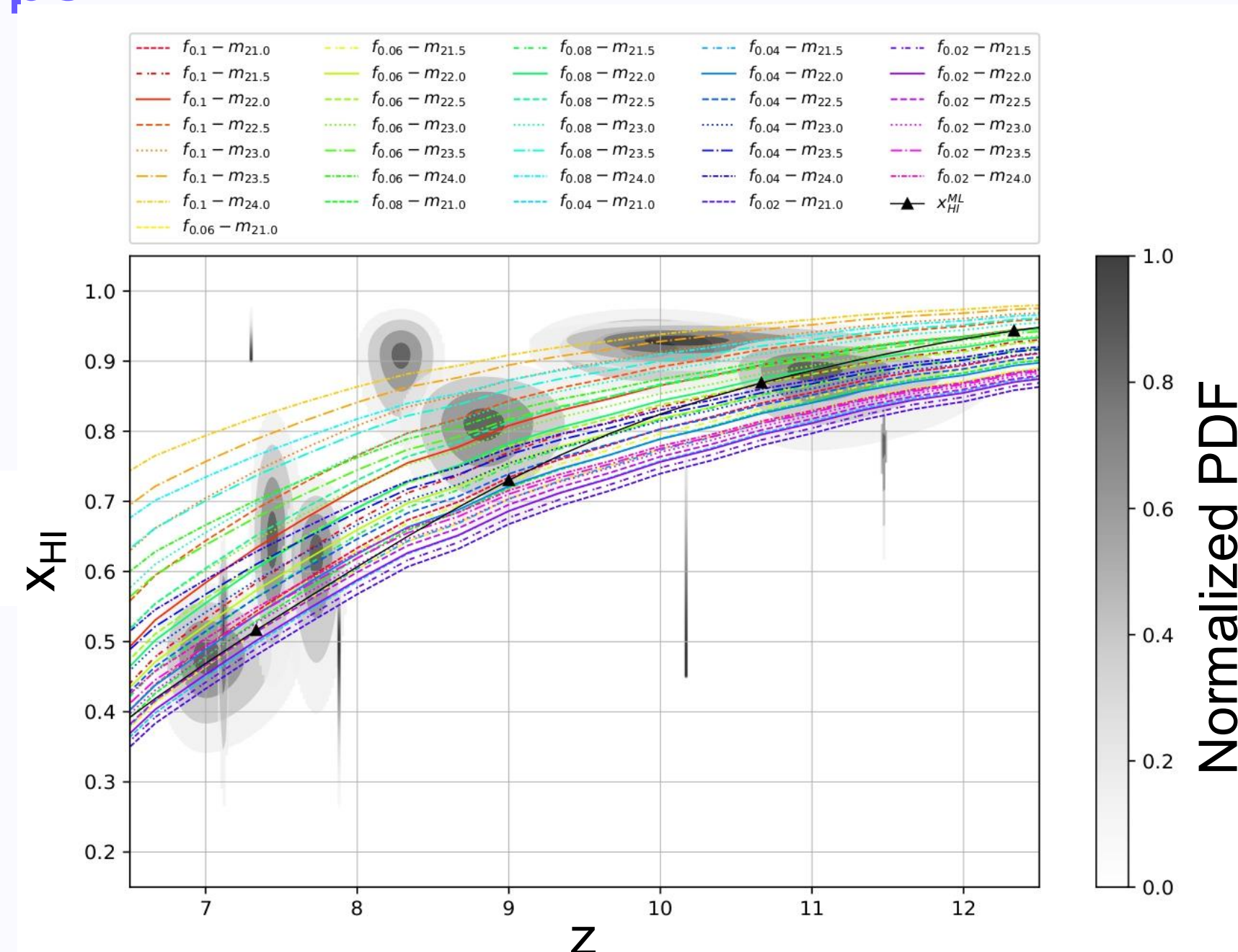
### Hybrid architecture used in the paper



Key design choice: observational uncertainty is carried through the model-selection pipeline instead of being collapsed to a single best-fit value.

## Results

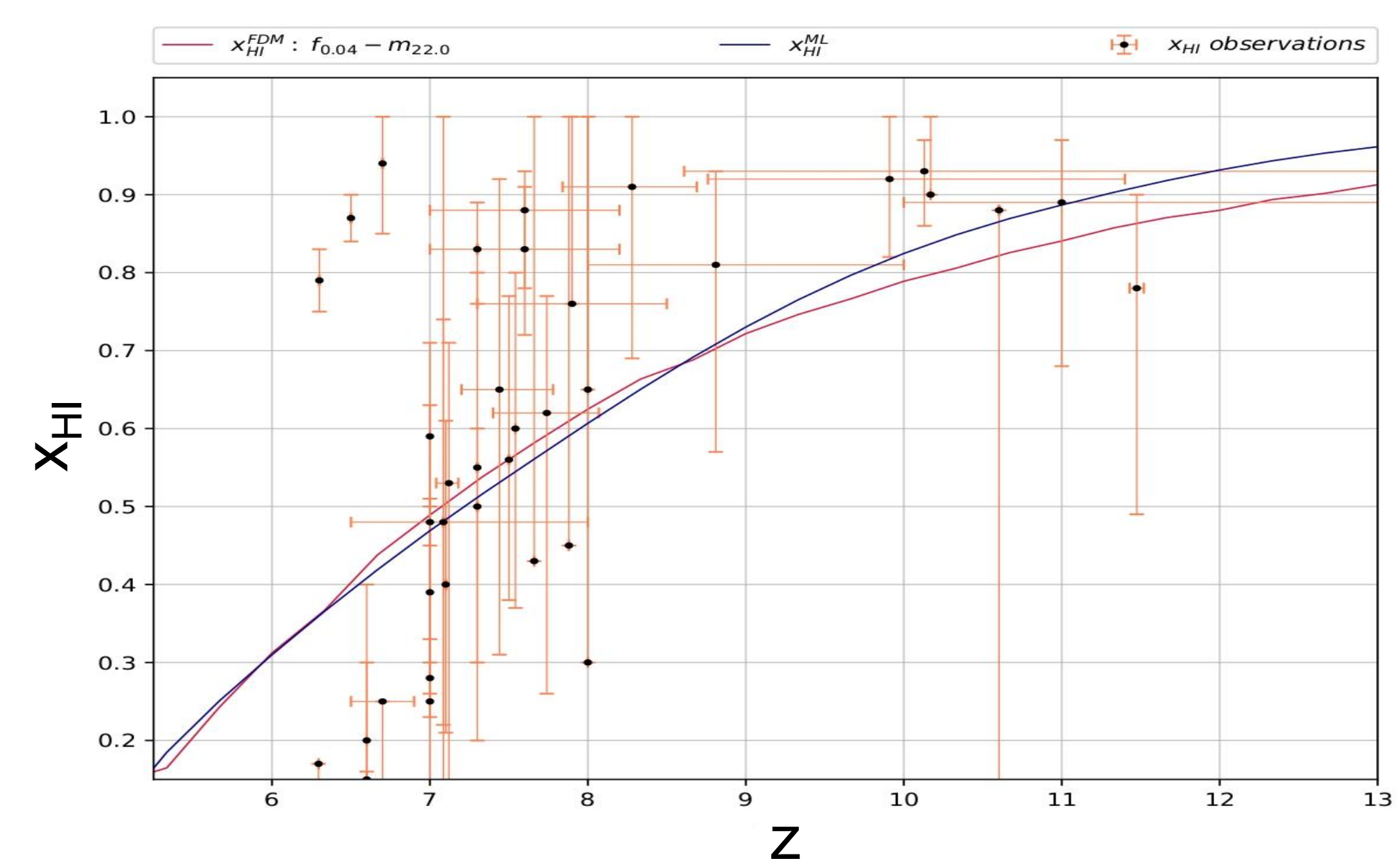
Fig. 1: The network tracks the JWST-informed posterior envelope.



Gray contours show credible regions from JWST-inferred  $x_{\text{HI}}$  posteriors. Colored dashed curves are 21cmFirstCLASS FDM histories, while the black curve is the hybrid posterior mean after uncertainty-aware fine-tuning. The overlap indicates that the learned trend remains consistent with the observational posterior envelope.

Takeaway: JWST-informed posteriors prefer a slower decline in  $x_{\text{HI}}$  at high redshift.

Fig. 2: Best-match model is near  $m_{\text{FDM}} \sim 10^{-22}$  eV and  $f_{\text{FDM}} \sim 0.04$ .



The pink simulation curve shows the minimum discrepancy relative to the hybrid model. The blue curve is the machine-learned trend; observational points. This preferred configuration tracks the central trend while remaining consistent with upper bounds.

This configuration gives the smallest discrepancy and tracks the JWST-informed trend with  $R^2 \sim 0.968$ .

## Physical implications & Consistency

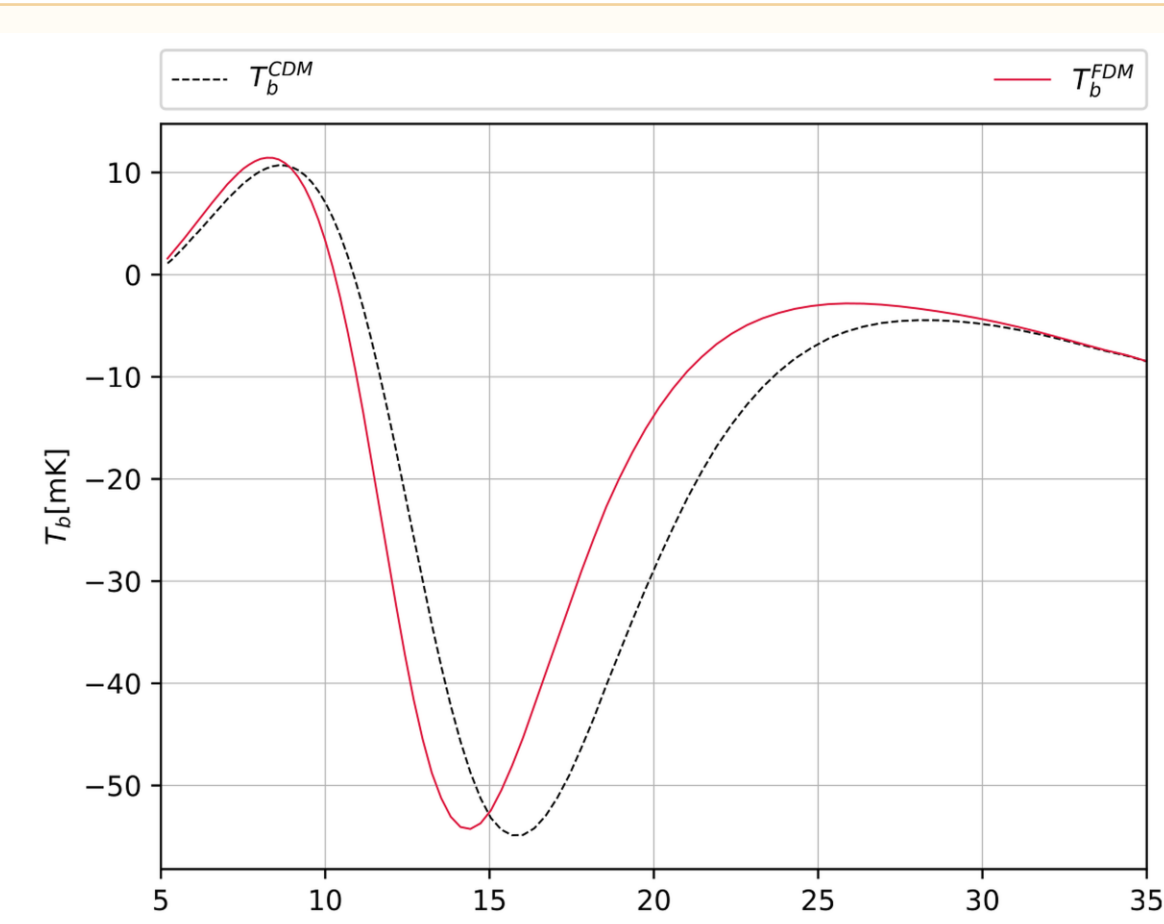


Fig. 3: Reionization becomes later and more gradual than in  $\Lambda$ CDM.

The preferred FDM case delays and smooths reionization instead of producing a rapid transition.

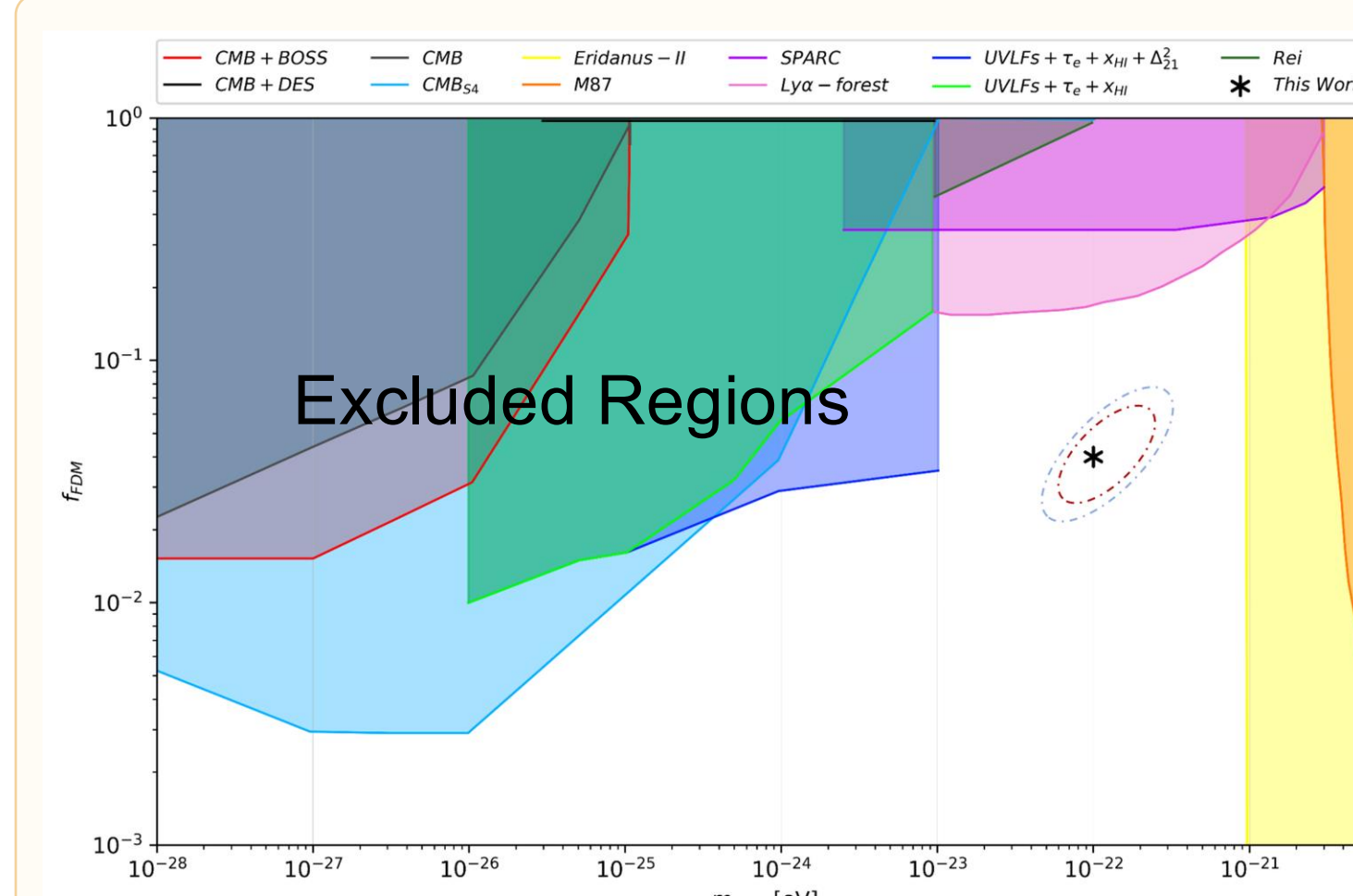


Fig. 4: The preferred parameter choice remains outside major excluded regions in literature [3].

Consistency check: favored parameters avoid over-suppressed structure growth and over-delayed reionization.

## Future work and takeaway

### Future possible work

- Combine JWST with 21 cm power spectrum, CMB optical depth, and UV luminosity functions.
- Build a unified uncertainty-aware likelihood to reduce astrophysical dark matter degeneracies.
- Apply simulation-based inference for stronger parameter constraints.
- Forecast performance for next-generation facilities such as SKA and HERA.
- Identify the observables most sensitive to dark matter microphysics.

### Final takeaway

Using JWST-informed uncertainty distributions, the study finds that an FDM model near  $m_{\text{FDM}} \sim 10^{-22}$  eV and  $f_{\text{FDM}} \sim 0.04$  best matches current reionization data. The result is both statistically favored and physically consistent with external constraints. This framework is not just a better fit; it turns the reionization era into a robust, testable laboratory for dark matter microphysics.

## Key references

[1] Hu, Barkana & Gruzinov 2000, Phys. Rev. Lett., 85, 1158.

[2] Flitter & Kovetz 2024, Phys. Rev. D, 109, 043513.

[3] Lazare, Flitter & Kovetz 2024, Phys. Rev. D, 110, 123532.