

Supplementary Information

1 Supplementary Information

Every procedure is in the Methods; the S-sections below hold the tables and robustness analyses that the Methods subsections and the main-text callouts defer to. S0 is the index.

1.1 S0. Reader’s map—which section answers which callout

Table S1

Looking for	Where
model provenance: checkpoints, loaders, envs	S1
test-set strata, counts, wave manifest	S2
relaxation protocol, formation energies, references	Methods B
single-point control, eqV2	Methods C
extended bootstrap intervals (phase 2)	S3
database DFT settings, +U exposure	S4
floor detail, MP metallic cut, Hegde	S5
trim-cutoff sweep	S6
Rung-0 constants, held-out, CHGNet decomposition	S7
the full leaderboard (Fig. 12)	S8
hull threshold sweep, like-for-like ceiling	S9
symprec sweep	S10
polymorph detail, Alexandria ceiling	S11
elastic no-+U recut, log-space, metals-only	S12
flag anatomy, panel robustness	S13
“do the flags distort the headline?”	S14
E_f binning, matched-E_hull, near-hull, OQMD cross-DB	S15
magnetism stratum	S16
cost / Pareto (Fig. 11)	S17
data and code availability	S18
AI assistance statement	S19

1.2 S1. Model provenance (model_provenance.md)

Model selection and the run protocol are Methods A. The table gives each potential’s exact loader, checkpoint, and isolating environment (envs/<name>), rebuilt from the registry `src/umlip_bench/potentials.py`; package version pins and checkpoint hashes ship with the released dataset.

Table S2

Model	Package	Loader / checkpoint	Env (envs/)
SevenNet-MF	sevens	7net-mf-ompa, modal_omat24	sevens
GRACE-2L	tensorpotential (TF)	grace_fm("GRACE-2L-OMAT", pad_atoms_ number=40)	grace
MACE-OMAT	mace-torch	mace_mp(model="medium-omat-0", default_ dtype="float64")	core
DPA-3	deepmd	DP(model="dpa3.pth")	deepmd
UMA	fairchem (v2)	uma-s-1p1, task_omat	fairchem
Orb-v3	orb-models	orb_v3_conservative_inf_omat (float32-high)	orb
eSEN	fairchem-core 1.10.0	facebook/OMAT24 : esen_30m_oam.pt (OCPCal- culator)	fairchem-v1
eqV2	fairchem-core 1.10.0	facebook/OMAT24 : eqV2_86M_omat_mp_salex. pt	fairchem-v1
MACE-MPA	mace-torch	mace_mp(model="medium-mpa-0", default_ dtype="float64")	core
MatterSim-5M	mattersim	MatterSim-v1.0.0-5M.pth	mattersim
M3GNet	matgl	M3GNet-PES-MatPES-PBE-2025.2 (stress_unit eV/Å ³)	matgl
CHGNet	chgnet	CHGNetCalculator (0.3.0)	core
SevenNet-0 †	sevens	7net-0	sevens
MatterSim-1M †	mattersim	default MatterSimCalculator	mattersim

† superseded within-family checkpoint; shown only in the closing leaderboard table (Fig. 12) and the eight-model elastic comparison. Three reproducibility caveats: the eSEN [1] and eqV2 [2] checkpoints come from the **gated facebook/**

OMAT24 Hugging Face repo [3] and load only through the legacy OCPCalculator in fairchem-core 1.10.0 (a separate environment from UMA’s fairchem v2); MACE runs in float64 because float32 stress noise stalls FIRE near minima; and M3GNet’s `stress_unit` must be eV/Å³ or ASE cell relaxation breaks silently.

1.3 S2. Test-set strata and counts

Test-set construction—scope, filters, strata, and sampling—is Methods A. **Strata and counts** (final manifest, `results/analysis/per_stratum.csv`):

Table S3

Stratum	What	Count
LIB2	binary intermetallic prototype decorations	202,724
LIB3	ternary intermetallic prototype decorations	1,178,736
unary	elemental reference states	30,808
E3 (lanthanide)	4f-alloy “edge of validity” probe	9,153
E1 / E1-ael	standard-DFT (no-U) nonmetals	5,818 / 470
E2 / E2-ael	+U entries (geometry only)	19,882 / 2,749
icsd_ael	AEL elastic subset	325 core †
overlap	ICSD alloys matched to a Materials Project entry	1,191
ln_unary / ln_alloy	trivalent-lanthanide references / alloys	956 / 3,189
quaternary	metal-only 4-component alloys	32
Total		1,456,033 (body rounds to 1.46M)

† The AEL-backed elastic set is 325 in the wave-1 core and grows to 3,544 once the E1/E2 AEL sub-strata are added; the elastic comparison of the main text’s §5 uses ~3,500 AEL structures across all admitted chemistries.

Construction in five waves. The manifest accumulated in five monotone waves (Methods A), entries selected by ascending `md5(auid)` so each wave is a strict superset of the last:

Table S4

Wave	Strata introduced	Entries
1	unary, lib2, lib3, icsd_ael, overlap	88,430
2	e1, e2, e3	16,956
3	exhaustive expansion of the prototype libraries	1,343,099
4	quaternary	32
5	ln_unary, ln_alloy	7,516
Total		1,456,033

From wave 3 on, geometries are taken inline from AFLUX [4] (`positions_fractional` plus cell parameters); the earlier waves use fetched POSCARs.

Two data-availability facts shaped the design. AFLOW’s own ICSD oxides are 97% already in MP, so an AFLOW oxide benchmark would add a second DFT answer but no new chemistry—hence the alloy-first scope. And AFLOW reports `enthalpy_formation_atom` for none of its +U intermetallics (0 of 4,579 LIB-matching +U entries), so the +U story is a geometry-and-methodology story, never a +U formation-energy comparison. Production ran the 1,456,033-entry manifest (~1.46M structures) against up to fourteen models at a ~0.03% hard-failure rate.

1.4 S3. Extended bootstrap intervals

The system-resampled bootstrap behind every “±” in the paper is Methods D. **Phase-2 intervals** (`scripts/bootstrap_ci_phase2.py`; same conventions—system-resampled, $B = 2000$, percentiles 2.5/97.5) extend it to the reference-free and elastic metrics:

Table S5

Metric	Model	Estimate	95% CI
Residual force, median max (eV/Å)	eqV2	0.00038	[0.00037–0.00039]
Residual force, median max (eV/Å)	eSEN	0.0217	[0.0214–0.0221]
Residual force, median max (eV/Å)	UMA	0.0401	[0.0394–0.0409]
Elastic G r , all-cut linear	MACE-MPA	0.160	[0.06–0.89]
Elastic G r , no-+U	MACE-MPA	0.965	[0.939–0.979]
Symprec retention gap UMA–GRACE, 0.1 Å	—	−0.017	[−0.043, +0.007]
Symprec retention gap UMA–GRACE, 0.01 Å	—	−0.160	[−0.207, −0.117]
Familiar–novel gap (meV/atom)	eqV2	+11.7	[10.6–12.9]
Familiar–novel gap (meV/atom)	CHGNet	+47.6	[44.8–50.4]

The residual-force top-three ordering is non-overlapping; MACE-MPA’s all-cut linear G r is outlier-dominated (the quantified log-space caveat of S12) while its no-+U recovery is robust; the 0.1 Å symprec gap crosses zero while the 0.01 Å gap is real (symprec uses $n = 300$, resampled over structures); and the familiar-vs-novel gaps all exclude zero.

1.5 S4. DFT settings of the four databases

The floor comparison rests on the four databases sharing PBE but differing in protocol. Settings compiled from the primary sources (docs/database_protocol_notes.md):

Table S6

Setting	AFLOW (LIB2/3)	Alexandria (PBE 3D)	OQMD	Materials Project
XC	PBE	PBE	PBE	PBE(+U)
ENCUT	AFLOW HT-standard	520 eV	max ENMAX of POT-CARs	520 eV
k-points	AFLOW HT-standard	KPPRA ≈ 1000	KPPRA 4000→8000	KPPRA ≈ 1000
+U	none (alloys)	oxides/fluorides (MP-style U)	correlated-TM oxides	oxides/fluorides (MP2020)
Elemental refs	raw DFT bulk elements	MP-compatible	FERE-style fitted	fitted / corrected
Post-hoc corrections	none	MP-compatible	FERE	MP2020 anion/+U mixing
VASP	HT-standard	5.2	5.3.2	—

AFLOW’s exact plane-wave and k-point settings are its high-throughput standard [5, 6] and we do not re-tabulate them. The operative rows are the last two: they are why Materials Project [7] is the outlier of Table 2 (Methods E), and why Alexandria—MP-pseudopotential-compatible yet raw-PBE on metals—lands with AFLOW, not with MP.

+U **exposure by scored population** (scripts/ldau_groupby.py). Every population the paper scores, grouped by AFLOW’s ldau_type flag; the operative fact is that the 1.38M core alloy libraries carry none:

Table S7

Population	+U fraction
Full benchmark (1.46M)	1.90%
e2 stratum	100%
e3 stratum	53%
ln_unary	11%
lib2/lib3 alloy libraries, unary, AFLOW $\cap$ MP overlap	0%
Alexandria-matched floor set	1.13%
OQMD-matched floor set	11.2%
AEL elastic set	78% (2,749 of 3,544)
Bad-reference flags (14,832 raw; 1,671 aligned)	0%

The no-+U cut of the elastic section (S12) is the remaining 795 structures.

1.6 S5. DFT-vs-DFT noise floor

The floor’s construction—fingerprint matching, estimator choice, and the two reality checks—is Methods E. **Pairwise disagreement** (Table 2 with the columns the body omits):

Table S8

Pair	median $ \Delta $ (meV/atom)	trimmed MAE (meV/atom)	removable per-element offset	shared metallic structures
AFLOW–Alexandria	6.0	23.9	none ($R^2 \leq 0.10$)	$\sim 343,000$
AFLOW–OQMD	8.1	26.3	none ($R^2 \leq 0.10$)	$\sim 12,900$
OQMD–Alexandria	7.7	27.8	none ($R^2 \leq 0.10$)	$\sim 34,000$
AFLOW–Materials Project	24.7	not reported †	~ 25 meV/atom residual, not removable ($R^2 \approx 0.10$)	$\sim 4,800$

$R^2 \leq 0.10$ in every row means composition explains almost none of the structure-to-structure disagreement; for MP a ~ 25 meV/atom median offset survives the fit.

† The AFLOW–MP trimmed-MAE floor is not reported: MP is the convention outlier, and its heavy tail is dominated by removable convention and bad-reference artifacts that a trimmed mean would misread as a raw-PBE floor. Quoting one would require first passing MP’s outlier tail through the bad-reference adjudication of Methods I; the tail-robust median (24.7) and the non-removable ~ 25 meV/atom residual are reported instead.

Per-element offset test (Methods E)—element sets. The metallic cut uses the nonmetal-exclusion set H, He, B, C, N, O, F, Ne, Si, P, S, Cl, Ar, Ge, As, Se, Br, Kr, Te, I, Xe, Po, At, Rn; the Fig. 1 floor-versus- E_{hull} binning uses a 22-element variant that counts Ge as a metal (both appear in the pipeline). The AFLOW $\cap$ MP metallic per-element $R^2 = 0.097$ was recomputed 2026-07-07 in the adjudication-robustness audit (`scripts/adjudication_robustness.py`).

Floor versus distance from the hull (Fig. 1). Binned against formation energy and against E_{hull} , the raw-PBE pairs hold a 5–11 meV/atom band out to $E_{\text{f}} \approx +750$ meV/atom and $E_{\text{hull}} \approx 800$ meV/atom (AFLOW–Alexandria, the largest sample, at 5–9 across its entire range); only the sparsest high- E_{f} AFLOW–OQMD bins ($n \leq 552$) rise to 12–15 meV/atom. The reference does not degrade appreciably far from equilibrium, and no single database is the noisy one.

The MP metallic-cut correction (Methods E), in numbers. The “removable convention” the first, contaminated decomposition found was dominated by O, S, and N offsets specifically; Hegde et al. [8] report median formation-energy disagreements of 105 meV/atom for AFLOW–MP and 87 for MP–OQMD against only 19 for AFLOW–OQMD.

1.7 S6. Trim-cutoff sensitivity

The 1 eV/atom trim (Methods D) removes only exceptional events, but its placement matters for the continuum-tailed mid-board: between cutoffs 0.25 and 1.0 eV/atom MACE-MPA’s trimmed MAE grows 62% and Orb-v3’s 56%, so the mid-board order is cutoff-sensitive while the leader and the tier structure are not. Trimmed MAE (relaxed protocol, meV/atom) at representative cutoffs (columns in eV/atom; `scripts/trim_sensitivity.py` $\rightarrow$ `trim_sensitivity.csv`):

Table S9

Model / DFT pair	0.25	0.5	1.0	2.0	5.0
eqV2	13.9	17.5	18.5	18.9	19.6
SevenNet-MF	21.5	26.4	28.2	28.9	29.6
GRACE-2L	23.2	28.1	29.8	30.4	31.3
MACE-OMAT	26.3	31.0	32.6	33.2	33.9
DPA-3	26.6	31.3	33.0	33.6	34.3
UMA	28.0	32.9	35.0	35.8	36.6
Orb-v3	22.9	30.3	35.8	37.6	38.6
eSEN	31.0	36.2	38.6	39.4	40.2
MACE-MPA	29.7	43.5	48.2	48.9	49.5
MatterSim-5M	43.8	49.5	51.6	52.3	53.1
M3GNet	51.7	59.1	63.2	64.6	65.4
MatterSim-1M $\dagger$	52.6	59.6	61.8	62.6	63.3
SevenNet-0 $\dagger$	70.5	83.4	87.0	88.1	88.8
CHGNet	98.8	121.1	126.5	127.6	128.4
<i>AFLOW–Alexandria floor</i>	14.3	20.3	23.9	25.2	25.5
<i>AFLOW–OQMD floor</i>	20.0	24.6	26.3	26.7	27.3
<i>OQMD–Alexandria floor</i>	18.6	23.3	27.8	29.3	29.9

$\dagger$ superseded checkpoints. The model ordering is invariant for every cutoff ≥ 1.0 eV/atom—below that, mid-board near-ties reorder (Orb-v3 moves three places between the 0.5 and 1.0 cutoffs; M3GNet and MatterSim-1M swap)—and the leader stays below the AFLOW–Alexandria floor throughout. At the untrimmed limit two checkpoints’ single corrupted rows dominate (GRACE 6.6×10^3 , SevenNet-0 4.0×10^7 meV/atom), which is why raw means are never reported; the full sweep including the untrimmed limit is plotted in `docs/figs/fig_trim_sensitivity.png`.

1.8 S7. Rung-0

The fit, its capacity bound, and the system-disjoint held-out split are Methods F.

Fitted per-element constants. The offsets are largest for the magnetic 3d elements, whose elemental reference differs most between conventions—Mn -118 , Cr -102 , Fe -77 meV/atom—with the non-magnetic metals near zero. These are the same constants that collapse the “bad reference” count in S13.

Held-out behavior (Methods F). Rung-0 leaves the OMat models slightly worse—the held-out penalty runs $+0.9$ to $+2.7$ meV/atom (eqV2 $18.5 \rightarrow 20.9$, SevenNet-MF $28.2 \rightarrow 30.7$, Orb-v3 $35.8 \rightarrow 38.5$; S8)—while the MP-trained models shed a large convention on top of a large genuine error (CHGNet $126 \rightarrow 73$, M3GNet $63 \rightarrow 57$, MatterSim $52 \rightarrow 43$). The full before/after table is Table 3; the held-out uncorrected MAE is within 0.6 meV/atom of the full-set value, so the before $\rightarrow$ after figures in the text use the full-set raw MAE.

CHGNet, decomposed. CHGNet’s large Rung-0 gain separates cleanly: a single global constant (-115.7 meV/atom, overbinding against its own unaries) accounts for most of it ($126.1 \rightarrow 82.3$ meV/atom), and element-specific offsets carry the rest, largest on the refractory metals.

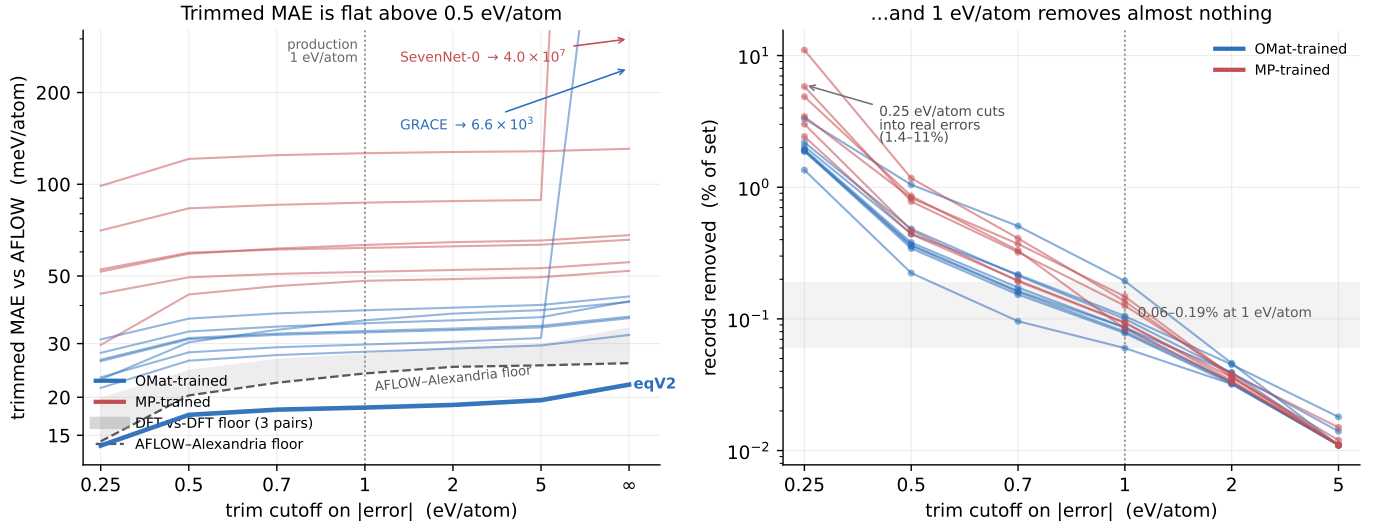


Figure S1: Trim-cutoff sensitivity: each model’s trimmed MAE against the $|\text{error}|$ cutoff, including the untrimmed limit where single corrupted rows dominate. The ranking is invariant for cutoffs at or above 1 eV/atom (Methods D).

Table S10

Element	Centered offset (meV/atom)
Ru	−168
W	−142
Os	−128
Mo	−99
Cr	−89

These offsets correlate with neither the MP–AFLOW nor the Alexandria–AFLOW per-element reference differences ($r = 0.11 / 0.18$), so they are CHGNet-specific systematic error, not an inherited database convention. This is the paradox Rung-0 is built to resolve: model errors can be strongly composition-linear (held-out R^2 up to 0.62 for the convention carriers) while metallic DFT-pair disagreement is not ($R^2 \leq 0.06$), so the same one-constant-per-element fit strips much from the former and nothing from the latter (`rung0_chgnet_diagnosis.csv`).

Robustness. A 5-fold system-disjoint cross-validation reproduces the 70/30 corrected MAEs within 0.2 meV/atom (fold sd 0.13–0.52), so the split is not load-bearing; a Huber refit ($\delta = 1.345 \cdot \sigma_{\text{MAD}}$) shifts absolute values down 0.4–5.6 meV/atom with rankings unchanged, and the OLS figures are quoted as the conservative choice (`scripts/rung0_robustness.py`).

1.9 S8. The full leaderboard (all metrics, fourteen models)

Figure 12 as a table: every model on every axis, with 95% system-resampled bootstrap half-intervals. Columns in paper order—raw MAE, single-point, after Rung-0, SP + Rung-0, hull-F1, E_{hull} MAE, residual force, polymorph ρ , no-+U shear. Dashes (—) mark metrics not run for a model—the shear column covers the eight elastic-task models on the no-+U cut, a panel that used the superseded MatterSim-1M checkpoint, so MatterSim-5M carries no shear value. The novel-vs-familiar gap is deliberately omitted as hull-distance-confounded (main-text §7).

Table S11

Model	Raw MAE (meV/atom)	Single-point (meV/atom)	After Rung-0 (meV/atom)	SP + Rung-0 (meV/atom)	Hull-F1	E_{hull} MAE (meV/atom)	Residual force (eV/Å)	Polymorph ρ	No-+U shear r
eqV2	18.5 ± 0.4	14.7 ± 0.3	20.9	15.6 ± 0.7	0.930 ± 0.005	17.3 ± 0.8	0.0004 ± 0.0000	0.983 ± 0.000	—
SevenNet-MF	28.2 ± 0.5	19.4 ± 0.3	30.7	19.6 ± 0.7	0.887 ± 0.006	24.4 ± 0.8	0.0435 ± 0.0010	0.960 ± 0.001	—
GRACE-2L	29.8 ± 0.5	21.0 ± 0.3	31.1	21.4 ± 0.7	0.870 ± 0.007	26.8 ± 0.8	0.0420 ± 0.0009	0.955 ± 0.001	0.984 ± 0.005
MACE-OMAT	32.6 ± 0.5	24.2 ± 0.3	33.5	23.5 ± 0.7	0.850 ± 0.008	29.3 ± 0.8	0.0447 ± 0.0010	0.946 ± 0.001	—
DPA-3	33.0 ± 0.4	23.9 ± 0.3	33.2	23.5 ± 0.6	0.842 ± 0.008	29.5 ± 0.8	0.0510 ± 0.0011	0.946 ± 0.001	—
UMA	35.0 ± 0.7	25.1 ± 0.7	29.2	14.2 ± 0.4	0.885 ± 0.010	23.7 ± 0.8	0.0401 ± 0.0007	0.966 ± 0.001	0.983 ± 0.008
Orb-v3	35.8 ± 0.6	20.2 ± 0.3	38.5	19.6 ± 0.7	0.878 ± 0.007	22.3 ± 0.8	0.0449 ± 0.0009	0.964 ± 0.001	0.983 ± 0.006
eSEN	38.6 ± 0.8	30.0 ± 0.8	29.5	15.9 ± 0.7	0.891 ± 0.009	25.6 ± 0.8	0.0217 ± 0.0004	0.971 ± 0.001	—
MACE-MPA	48.2 ± 1.7	39.1 ± 1.7	35.3	23.1 ± 0.7	0.851 ± 0.008	42.4 ± 1.6	0.0466 ± 0.0011	0.944 ± 0.001	0.977 ± 0.007
MatterSim-5M	51.6 ± 0.5	39.1 ± 0.4	43.2	32.8 ± 0.7	0.773 ± 0.011	46.1 ± 0.8	0.0520 ± 0.0012	0.905 ± 0.001	—
M3GNet	63.2 ± 0.6	50.1 ± 0.5	56.9	46.4 ± 0.8	0.670 ± 0.012	54.0 ± 0.8	0.0958 ± 0.0024	0.868 ± 0.002	0.848 ± 0.034
MatterSim-1M †	61.8 ± 0.6	48.4 ± 0.5	55.6	45.3 ± 0.7	0.671 ± 0.012	54.6 ± 0.9	0.0893 ± 0.0023	0.868 ± 0.002	0.938 ± 0.030
SevenNet-0 †	87.0 ± 1.0	66.1 ± 0.8	64.4	55.1 ± 1.1	0.627 ± 0.012	69.8 ± 1.0	0.1067 ± 0.0029	0.833 ± 0.002	0.923 ± 0.017
CHGNet	126.5 ± 1.1	101.6 ± 0.9	72.9	61.3 ± 1.1	0.541 ± 0.013	92.5 ± 1.1	0.0980 ± 0.0024	0.825 ± 0.002	0.878 ± 0.030

± are 95% system-resampled bootstrap half-intervals ($B = 2000$; `bootstrap_ci_all.csv`, `bootstrap_ci_phase2.csv`, `bootstrap_ci_sprung0.csv`). † superseded checkpoints. The After-Rung-0 column carries no interval—no committed bootstrap covers the relaxed+Rung-0 combination—and the two Rung-0 columns are scored on the 30% held-out systems (per S7 the held-out uncorrected MAE is within 0.6 meV/atom of the full-set value, so the columns are comparable but not computed on identical sets). The shear column is the log-space r of S12 (`elastic_logspace.csv`). eqV2’s

polymorph and residual-force intervals render as ± 0.000 because the bootstrap collapses at a plateau (residual-force CI [0.00037, 0.00039]).

The fully-controlled energy order, resolved. Bootstrap CIs on the SP + Rung-0 column (Table 3), paired over the shared held-out systems (the correct test, since the models’ errors on a common structure set are highly correlated; `scripts/bootstrap_ci_sprung0.py`), have marginal half-widths of ± 0.4 – 0.7 meV/atom and paired differences that both exclude zero:

Table S12

Paired difference (meV/atom)	Estimate	95% CI
UMA – eqV2	–1.38	[–1.76, –0.99]
eqV2 – eSEN	–0.33	[–0.39, –0.27]

The fully controlled order is therefore a strict $\text{UMA} < \text{eqV2} < \text{eSEN}$, with UMA formally lowest—but these intervals do not propagate the Rung-0 fit’s own per-model noise (the $+0.9$ to $+2.7$ meV/atom held-out penalties of S7, the same few-meV scale as the differences), and the entire spread is under 2 meV/atom, far below the 24–28 meV/atom trimmed-MAE floor: the ordering is at best statistically resolvable and physically meaningless—the paper’s own thesis, applied to its energy board.

1.10 S9. Hull-F1 robustness

Hull construction, the stability window, and the validation against pymatgen are Methods G.

Threshold sweep (`scripts/hull_f1_threshold_sweep.py`). eqV2 leads at every tolerance, and the chase pack (F1 0.84–0.89 at the 25 meV/atom operating point) swaps order across thresholds without resolving—eSEN leads it at 5 meV/atom, SevenNet-MF at 50. Hull-F1 at four stability windows:

Table S13

Model	5 meV/atom	10	25	50
eqV2	0.885	0.914	0.930	0.938
eSEN	0.859	0.874	0.891	0.898
SevenNet-MF	0.840	0.858	0.887	0.905
UMA	0.842	0.860	0.885	0.901
Orb-v3	0.830	0.853	0.878	0.902
GRACE-2L	0.814	0.840	0.870	0.889
MACE-MPA	0.798	0.820	0.851	0.871
MACE-OMAT	0.786	0.811	0.850	0.873
DPA-3	0.778	0.807	0.842	0.869
MatterSim-5M	0.724	0.748	0.773	0.804
MatterSim-1M †	0.599	0.624	0.671	0.730
M3GNet	0.581	0.618	0.670	0.732
SevenNet-0 †	0.545	0.573	0.627	0.688
CHGNet	0.477	0.506	0.541	0.607

Like-for-like ceiling. Table 4’s Alexandria row (hull-F1 0.906) is computed on a different structure set than the model rows. Recomputed on the shared $\text{AFLOW} \cap \text{Alexandria}$ overlap (`scripts/alex_ceiling_shared.py`) the ceiling is 0.895 and the four leading models clear it: eqV2 0.943, eSEN 0.914, SevenNet-MF 0.914, UMA 0.910. eqV2 above the ceiling is protocol proximity, not super-DFT physics—fine-tuned on subsampled Alexandria, it matches AFLOW’s raw-PBE convention more closely than a second independently run DFT database does.

1.11 S10. Space-group retention versus symprec

The tolerance problem and the four-model 300-structure sample are Methods G. Retention at each tolerance (`scripts/aggregate_symprec.py`):

Table S14

Model	symprec 0.01 Å	0.05 Å	0.10 Å
UMA	0.78	0.89	0.90
Orb-v3	0.84	0.89	0.89
GRACE-2L	0.94	0.92	0.92
CHGNet	0.94	0.94	0.92

UMA’s and Orb-v3’s retention *rises* as the tolerance loosens while GRACE’s and CHGNet’s stays flat—the mechanism behind the gap collapse Methods G reports: the dramatic version of the gap is a symprec artifact, and only a small genuine fidelity difference remains.

1.12 S11. Polymorph ordering in detail

The metric—Spearman ρ and ground-state hit rate per qualifying composition—is Methods G. Per-model medians at the three AFLOW-spread thresholds (`scripts/analyze_polymorph_ranking.py`):

Table S15

Model	median ρ (spread ≥ 25 / 50 / 100 meV/atom)	ground-state hit rate (25)
eqV2	0.98 / 0.98 / 0.98	0.57
eSEN	0.97 / 0.97 / 0.97	0.54
UMA	0.97 / 0.97 / 0.97	0.53
Orb-v3	0.96 / 0.96 / 0.96	0.51
SevenNet-MF	0.96 / 0.96 / 0.96	0.51
GRACE-2L	0.95 / 0.95 / 0.96	0.51
MACE-OMAT	0.95 / 0.95 / 0.95	0.48
DPA-3	0.95 / 0.95 / 0.95	0.48
MACE-MPA	0.94 / 0.94 / 0.94	0.48
MatterSim-5M	0.90 / 0.90 / 0.91	0.42
M3GNet	0.87 / 0.87 / 0.87	0.36
MatterSim-1M †	0.87 / 0.87 / 0.87	0.36
SevenNet-0 †	0.83 / 0.83 / 0.83	0.33
CHGNet	0.83 / 0.83 / 0.83	0.31

The two-tier divide is robust to the threshold: OMat-trained models at median ρ 0.95–0.98, MACE-MPA at 0.94, the MP-trained generation at 0.83–0.91. The ground-state hit rate is humbling for all: asked to name the single lowest-energy polymorph, the leader is right 0.57 of the time and CHGNet 0.31, against a random-guess baseline of 0.073 (median 25 polymorphs per composition). The models capture the *shape* of the landscape while missing its exact minimum, because the lowest-lying polymorphs sit within the DFT-vs-DFT floor of one another: the Alexandria ceiling is top-1 0.880 at median ρ 0.994, and eqV2 on the identical members reaches top-1 0.92, ρ 1.00.

1.13 S12. Elastic response

The finite-strain protocol and the U-status stratification are Methods H. **Shear correlation before and after re-moving +U structures** (Fig. 6; `scripts/elastic_logspace.py`, `elastic_noU_wrangle.py`; the linear no-+U value for SevenNet-0, a superseded checkpoint, was dropped from the recut):

Table S16

Model	Pearson r, all AEL	r, no-+U (~795)	log-log slope (no-+U)	mult. bias (no-+U)
MACE-MPA	0.16	0.97	~1.0	0.97
CHGNet	0.51	0.83	~1.0	0.48
M3GNet	0.46	0.72	~1.0	0.71
SevenNet-0	~0.53	—	~1.0	0.73
UMA	0.83	0.99	0.91–1.02	0.97–1.03
Orb-v3	0.86	0.98	0.91–1.02	0.97–1.03
GRACE-2L	0.80	0.85	0.91–1.02	0.97–1.03

Bulk modulus tracks AFLOW for every model (r 0.78–0.98); the shear story is the +U story. On the no-+U subset every model’s log-log slope lies between 0.91 and 1.02, so the residual “softening” of the older models is a uniform multiplicative bias (CHGNet 0.48 $\times$, M3GNet 0.71 $\times$, SevenNet-0 0.73 $\times$), not a slope deficit. MACE-MPA’s headline r = 0.16 was itself partly a statistic’s artifact: its full-set median multiplicative bias is 0.97 and its log-space correlation 0.92, so the collapse is what a small +U-concentrated population of catastrophic misses does to a linear correlation.

Metals-only recut. The AEL ground truth lives mostly on ICSD nonmetal compounds; only 1,259 of the 3,544 AEL structures (and 126 of the 795 no-+U ones) are purely metallic (`scripts/elastic_metals_recut.py`). Restricting to metals leaves the conclusion intact—+U-stratified shear correlations run 0.85–0.99 and the MP generation’s +U sensitivity if anything sharpens—but at far lower statistical power, so the main text reports the full AEL set and this recut is the honest metals-only check.

1.14 S13. Bad references—anatomy of the flags

The consensus detector, its thresholds, the per-element re-referencing, the adjudication protocol, and the adjudication verdicts are all Methods I; this section holds what the flags *are*, plus one adjudication-provenance caveat.

Flag geometry. The failure is one-sided and structural—geometric, not energetic (`scripts/badref_characterize.py`, `badref_alex_geom_scan.py`). Of the 14,832 raw flags, 1,671 survive the per-element re-alignment (Methods I); AFLOW sits high in 99.7% of raw flags (median AFLOW – consensus +403 meV/atom raw, +1,085 aligned). The flagged structures depart sharply from the benchmark background in geometry, not just energy—volume per atom differs from the Alexandria partner by 22.3% against a 0.32% background, and model relaxations move the cell by 23–29% against 0.4–1.4%. The destination join is the near-proof of a wrong-branch reference: where Alexandria’s volume differs from AFLOW’s by more than 10%, 84% of model relaxations land within 10% of Alexandria’s volume, and the flags’ single-point errors (243–448 meV/atom) are roughly 3–5 $\times$ smaller than their relaxed ones (2.7–4.9 $\times$ per model)—AFLOW’s energy is roughly right for a wrong structure.

Two systematic families dominate the aligned set. Three AB₂ *Fmmm* decorations (space group 69, Wyckoff patterns 1b,2i, 1a,2i, 1a,2f,2i) hold 460 of the 1,671 aligned flags—a 30.1% flag rate on a 1,526-member family, $\sim 260\times$ the base rate, while the other 1,197 SG-69 structures carry only 7—a chemistry-dependent relaxation collapse leaving over-compressed published cells the models re-expand by a median +73%, enriched on Sn (7 $\times$), Be (4.5 $\times$), and Ba (4 $\times$). Duplicated broken unaries make up another 14% of aligned flags (identical stuck copies, E_f +450 to +1,204 meV/atom, volumes 11–21% above the ground state). The reverse population—where a third database sides with AFLOW and the models are wrong together—is 536 of 4,847 adjudicable raw flags (11%), concentrated in the 4d/5d refractories (Ir, Os, Tc, Re) with unremarkable geometry (median signed ΔV +0.6%): an energy-only collective miss consistent with shared training-reference conventions, on the same refractory elements that dominate CHGNet’s fitted offsets (S7).

Panel-expansion robustness. Rebuilding the consensus detector on all fourteen models (`scripts/consensus_panel14.py`) gives 15,190 flags at 90.3% Alexandria pro-model against the production 8-model era’s 14,832 at 88.9%, retaining 91.9% of the production flags (Jaccard 0.83); the paper’s quoted counts stay with the production detector. The original adjudication matched 1,402 structures at 95%; its intermediate join tables were lost to scratch-space purging, and the committed strict-prototype reconstruction recovers 404 of them at a consistent 91%—both numbers are reported.

1.15 S14. Do the flags distort the headline numbers?

Barely, and symmetrically. The 1 eV/atom trim already removes about half of the raw flags; excluding the surviving 1,671 outright moves every model’s trimmed MAE by less than 0.4 meV/atom. Excluding all 14,832 raw flags moves the models by 3.2–3.9 meV/atom and the like-for-like floor by 2.3—both sides shift together and no ranking changes (`scripts/build_badref_exclusions.py`). Because the flags are reference-convention artifacts present on both sides of the model-versus-floor comparison, removing them can neither manufacture nor erase a model’s standing. Hull-F1 is immune: only 2–3 of the 24 hull-poisoning too-low flags survive any leader’s kept set, and the recomputed F1 is unchanged to four decimals (`badref_hull_sensitivity.csv`). The two surgical exclusion rules are materialized in `badref_exclusions.csv`—the three-pattern SG-69 family (1,612 structures across all strata, a flag-then-inspect superset of the 1,526 counted above) and a keep-one-representative dedup of broken unary copies (11,477 entries)—but headline metrics in this paper are computed on the full test set, and the list ships with the reproduction repository as a robustness artifact whose adoption as a default filter is left to future revisions.

1.16 S15. Familiarity, novelty, and generalization

The familiarity fingerprint, the matched-E_{hull} control, the near-hull comparison, and the OQMD campaign design are Methods J.

Formation-energy binning (the SI form of Figs. 8–9; `scripts/analyze_err_vs_ef.py` $\rightarrow$ `results/analysis/error_vs_ef.csv`; figure docs/figs/fig_err_vs_ef.png). Binned in 50-meV slices of AFLOW E_f (73 bins per model with ≥ 100 structures each, -1.1 to $+2.7$ eV/atom), every model’s median $|\text{error}|$ climbs with formation energy: the Spearman correlation between per-bin median error and bin center is:

Table S17

Model	ρ	Model	ρ
SevenNet-0 †	0.99	eSEN	0.92
M3GNet	0.97	GRACE-2L	0.91
MACE-MPA	0.97	eqV2	0.87
CHGNet	0.96	MatterSim-5M	0.84
MACE-OMAT	0.93	Orb-v3	0.80
DPA-3	0.93	SevenNet-MF	0.78
MatterSim-1M †	0.92	UMA	0.69

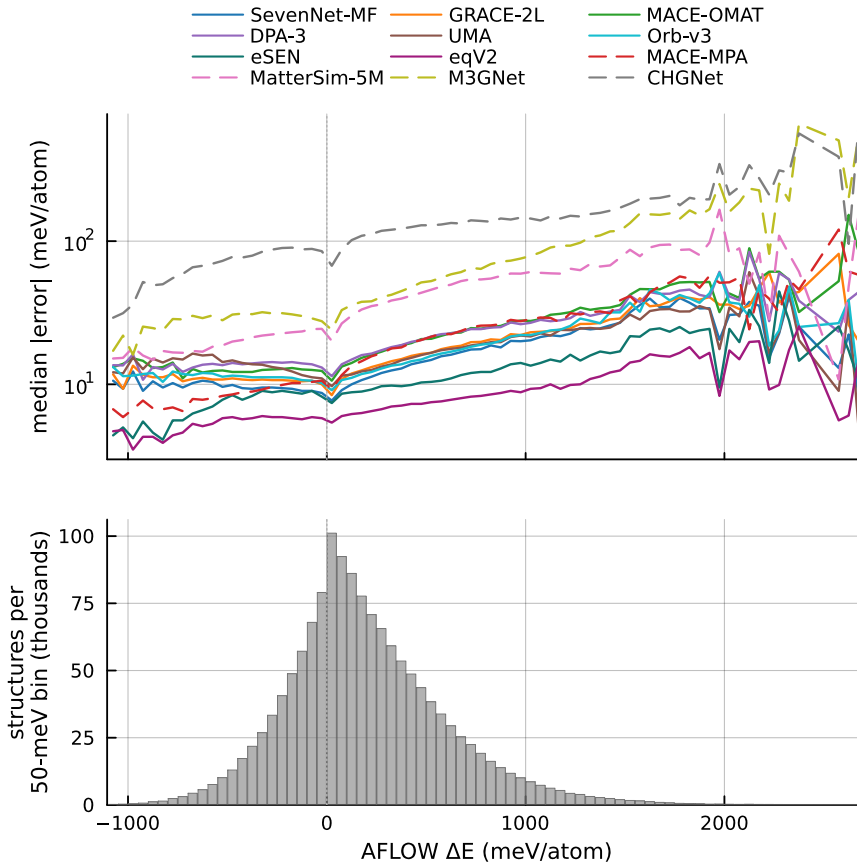


Figure S2: Median formation-energy error against AFLOW formation energy in 50-meV/atom bins (the SI form of main-text Figs. 8–9): every model’s error climbs with formation energy (Methods J).

Ten of the fourteen sit at 0.84–0.97; the three low outliers (Orb-v3, SevenNet-MF, UMA) go noisy only in the sparse bins above +2 eV/atom—restricted to $E_f \leq 2$ eV/atom, all fourteen sit at 0.81–0.99, the numbers the main text quotes.

The rise tracks the sign of the energy, not its magnitude: at matched $|E_f| \approx 1$ eV/atom (bins centered -975 vs $+975$ meV/atom), median error is 1.4 – $4.7\times$ larger on the unfavorable side (panel median $2.9\times$; MACE-MPA $6.7 \rightarrow 27.6$ meV/atom, CHGNet $36.1 \rightarrow 146.0$, eqV2 $3.5 \rightarrow 8.8$; smallest UMA $15.4 \rightarrow 21.9$). And E_{hull} is the sharper axis (`scripts/analyze_err_vs_hull.py` $\rightarrow$ `err_vs_hull.csv`, `quartiles_ef.csv`, `quartiles_ehull.csv`): across the ten E_{hull} bins (edges 0–6,400 meV/atom) all fourteen models are monotonic to Spearman 0.99–1.00, and the lowest-to-highest E_{hull} quartile gives the main text’s Fig.-9 numbers exactly—SevenNet-MF $7.3 \rightarrow 16.4$ meV/atom, MACE-MPA $7.5 \rightarrow 22.6$, CHGNet $51.2 \rightarrow 133.6$ —while the same models binned on E_f quartiles start higher and rise less cleanly ($9.1 \rightarrow 16.3$, $9.3 \rightarrow 22.3$, $81.3 \rightarrow 127.4$, the first two E_f quartiles non-monotonic for SevenNet-MF and CHGNet).

Formation-energy distribution (Fig. 8; `ef_dist_compare.csv`, `ef_overlap_compare.csv`, `oqmd_metals_ef_dist.csv`; full-OQMD pipeline in `scripts/oqmd_dump/`). On the committed 50-meV histograms: AFLOW’s deduplicated metals (1,042,241 entries) put 71.2% of structures above zero with the median in the +150–200 meV/atom bin (the caption’s unbinned +172); Alexandria’s AFLOW-overlapping metals track that shape at 70.5% above zero; and OQMD’s complete metallic set (111,901 entries from the qmpy dump) sits at 66.6% above zero with its median in the same bin (the caption’s +159)—three independently constructed databases agree that the combinatorial libraries skew unfavorable. (Provenance: the exact medians +172/+159 and the 343k Alexandria-overlap and 111,901 OQMD counts come from the cluster-side unbinned dumps documented in `scripts/oqmd_dump/README.md`; the committed 50-meV histograms reproduce the binned distribution.) The scored benchmark itself (`ef_dist.csv`, 1,420,601 structures) is marginally less skewed: 68.8% above zero, median bin +100–150. The AFLOW–Alexandria floor stays flat along the same axis (per-structure median $|\Delta E_f|$ 5.1–7.5 meV/atom in every 250-meV E_f bin from -1.0 to $+1.5$ eV/atom, 8.4 only in the sparsest bin at $n = 173$; `floor_vs_ef.csv`, the E_f -axis companion of S5’s Fig. 1), so the error that rises with formation energy belongs to the models, not to the benchmark.

Matched- E_{hull} re-binning (`scripts/matched_ehull_generalization.py`; the control of Methods J), per model: eqV2 $+11 \rightarrow +1.2$, SevenNet-MF $+15 \rightarrow +1.0$, GRACE $+16 \rightarrow +1.5$; the convention carriers eSEN and UMA start at $+20$ and $+10$ and collapse only once Rung-0 is applied (eSEN $+20.2 \rightarrow -0.8$, UMA $+10.0 \rightarrow +0.1$). Neither confound alone accounts for the gap; both together erase it.

Near-hull disagreement (Fig. 10; `scripts/near_hull_dft_floor.py`; design in Methods J). The window’s DFT

floor is median 5, mean 10 meV/atom. Beyond eqV2 riding that floor: MACE-MPA and UMA carry heavier tails of 0.1–1 eV/atom misses while SevenNet-MF, Orb-v3, and MACE-OMAT decay cleanly, and the DFT pair’s own tail is flat past 100 meV/atom—even two careful databases carry a small catastrophic-disagreement population.

OQMD cross-database campaign (`scripts/analyze_oqmd_aligned.py`, `analyze_oqmd_metals.py`; design in Methods J), per model on the 12,409-compound covered set: UMA 21, SevenNet-MF 23, GRACE 25 meV/atom—the same leading group as the re-referenced AFLOW board; M3GNet 63 and CHGNet 64 trail—the leaderboard is a property of the models, not of AFLOW.

1.17 S16. Magnetism

Magnetic systems are a labeled stratum, never pooled into the nonmagnetic headline. MACE-MPA is the instructive case: it classifies stability as well as the OMat models yet carries its largest errors on magnetic intermetallics (magnetic vs non-magnetic trimmed MAE 90.4 vs 37.4 meV/atom (`results/analysis/magnetic_slice.csv`)), the same magnetic-3d reference convention that S7 and S13 remove. Reported separately so it never blurs the metallic headline.

1.18 S17. Compute cost and the Pareto frontier

Cost measurement—core-seconds, the matched CPU re-measure for the GPU-run models, and eqV2’s exclusion—is Methods K. The efficient set depends on the metric (Fig. 11): Orb-v3 and UMA hold the mid-cost frontier for hull-F1, polymorph ordering, and forces; eSEN (~73 core-seconds, the most expensive) buys the high-accuracy tip of all three; DPA-3, MACE-OMAT, and SevenNet-MF carry the raw-energy frontier; the cheap M3GNet and MatterSim anchor every frontier, and CHGNet is dominated throughout.

1.19 S18. Data and code availability

The FAIR dataset and analysis-code release are described in Methods K. Each figure’s generating script is named in its caption or the relevant SI section; model checkpoints and environment pins are in S1.

1.20 S19. Use of AI assistance

The use-of-AI disclosure is given in Methods §L.

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