

Modeling-Making-Modulating High-Entropy Alloy with Activated Water-Dissociation Centers for Superior Electrocatalysis

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Abstract

High-entropy alloys have recently emerged as promising electrocatalysts for complex reactions owing to their tunable electronic structures and diverse, unique binding sites. However, their vast compositional space, both in terms of elemental variety and atomic ratios, presents a major challenge to the rational design of high-performance catalysts, as experimental efforts are often hindered by ambiguous element selection and inefficient trial-and-error methods. In this work, a bottom-up research strategy using machine learning-assisted first-principles calculations was applied to accelerate the design of quinary high-entropy alloys toward efficient multi-electron transfer reactions. Here, we report the design of PtPdRhRuMo, which exhibits key physicochemical properties favoring methanol oxidation reaction. Notably, the incorporation of Mo as the fifth element significantly activates specific binding sites on HEA surfaces, enhancing methanol adsorption and, in particular, water dissociation ability. This facilitates hydroxyl species formation, which effectively mitigates CO intermediate adherence while promoting the complete oxidation of CH₃OH to CO₂ via alternative reaction pathways. Guided by theoretical predictions, experimental samples with different morphologies of mesoporous PtPdRhRuMo catalyst (m-HEANP(Mo) nanoparticles and m-HEAF(Mo) thin film) were then synthesized, demonstrating superior electrocatalysis with a large current density of up to 18.20 mA cm⁻² and mass activity of 9.89 A mg_{Pt}⁻¹, alongside the long-term durability for efficient methanol electrooxidation applications.

KEYWORDS: High-entropy alloys; Electrocatalyst; Machine learning; Mesoporous nanostructure; CO poisoning; Water dissociation; DFT calculations; Methanol oxidation

Introduction

Platinum-group metals (PGMs) are widely recognized in electrocatalytic processes for their exceptional activity and chemical stability¹. However, these single metallic systems could only perform a specific reaction and often expose limitations in complex reactions requiring multiple electron transfer steps, such as the methanol oxidation reaction (MOR) involving six-electron transfers. While Pt is the most active commercial catalyst for MOR, its catalytic performance is largely hindered by susceptibility to CO poisoning, a notorious intermediate that blocks Pt active sites, resulting in a gradual decline in efficiency over time²⁻⁴. Therefore, developing electrocatalysts with optimal performance and good CO-resistance is essential for methanol conversion applications. Current strategies suggest alloying Pt with other transition metals might address these challenges²⁻⁶.

Despite their relatively recent emergence in 2004, high-entropy alloys (HEAs) have rapidly gained significant attention in the catalysis field⁷⁻⁹. The integration of five or more metal elements in HEAs not only fine-tunes the electronic structure but also creates random atomic arrangements, providing distinct and diverse surface binding sites that significantly enhance catalytic activity compared to single metals, binary alloys, and medium-entropy alloys (MEAs)⁹. Additionally, their diverse atomic environment produces a complex energy landscape, leading to a sluggish diffusion effect that mitigates degradation and dissolution over time more effectively than single-metal catalysts⁸. Since multiple elements of HEA can work synergistically, its performance and functionality are highly promising for complex reactions like MOR. Nevertheless, current research on HEAs electrocatalysts has primarily focused on experimental efforts^{4,10-12}, often with unclear and somewhat random element selection. It was reported that catalysts containing Pt/Pd are efficient for oxygen reduction and hydrogen evolution reactions^{13,14}, while Ru/Ir-involved excels in oxygen evolution reactions^{15,16}, and Cu-involved is particularly effective for CO₂ reduction reactions¹⁷. Compared to these reactions, the MOR process is less well understood due to the complicated reaction pathways with various intermediates² (dual CO- and CO-free pathways, see **Figure S1**). This leaves questions about the roles of elements and which combinations are optimal for achieving efficient MOR performance. While tailoring atomic ratios could further enhance catalytic performance, the vast compositional space of HEAs poses an additional challenge. For instance, varying the composition of each metal in a five-element HEA from 2-92% in 2% increments results in 211,876 possible combinations. Experimentally exploring such a large number of possibilities is both expensive and unrealistic if based solely on human chemical intuition. To reduce experimental trial and error efforts, a tight combination between first-principles calculations and machine learning techniques is essential in unveiling the catalytic process and guiding material design, significantly accelerating the exploration of HEA catalysts in a more effective way.

In this work, we perform a bottom-up strategy to design high-performance HEA electrocatalysts, progressing from computational quantum simulations to experimental lab validation (see **Figure 1a**). Theoretical design begins with selecting critical elements that form the basis of the alloy. Four PGM elements, i.e., Pt, Pd, Rh, and Ru, were chosen for their high catalytic activity, similar atomic radii and electronegativity, and their ability

to form a stable, well-mixed solid solution with a face-centered cubic (fcc) structure. To achieve high MOR performance, the fifth element, X, was screened from a pool of neighboring elements (i.e., Ir, Os, Au, Cu, Ni, Mo, and Cd) with similar characteristics to render durability and create multi-active centers leveraging the high entropy effects of the quinary alloy PtPdRhRuX. These selected elements are feasible for co-reduction and alloy formation using our low-temperature synthesis yet ensure diverse electronic and chemical properties, spanning noble metals (Ir, Os, Au), non-noble transition metals (Ni, Cu), an early transition metal (Mo), and a post-transition metal (Cd). Guided by machine learning-assisted first-principles predictions, the PtPdRhRuMo alloy was identified as the most promising high-entropy alloy candidate, featuring numerous physicochemical properties favorable for MOR applications. These theoretical predictions were subsequently translated into experimental testing, confirming the superior electrochemical performance of PtPdRhRuMo. Accordingly, the quinary HEA-PtPdRhRuMo catalysts demonstrated not only remarkable long-term durability (maintaining approximately 48% of their initial activity after 10,000 s) but also high catalytic performance, with electric current values of up to 18.20 mA/cm² and 9.89 A mg_{Pt}⁻¹ for the film sample, and 12.02 mA/cm² and 7.70 A mg_{Pt}⁻¹ for the nanoparticle sample. These results significantly outperform those of high entropy alloys based on other metals, medium-entropy alloy counterparts, commercial Pt-C, and the most recently reported Pt-based catalytic systems for efficient methanol electrooxidation applications.

Results and discussion

Computational screening of PtPdRhRuX electrocatalysts

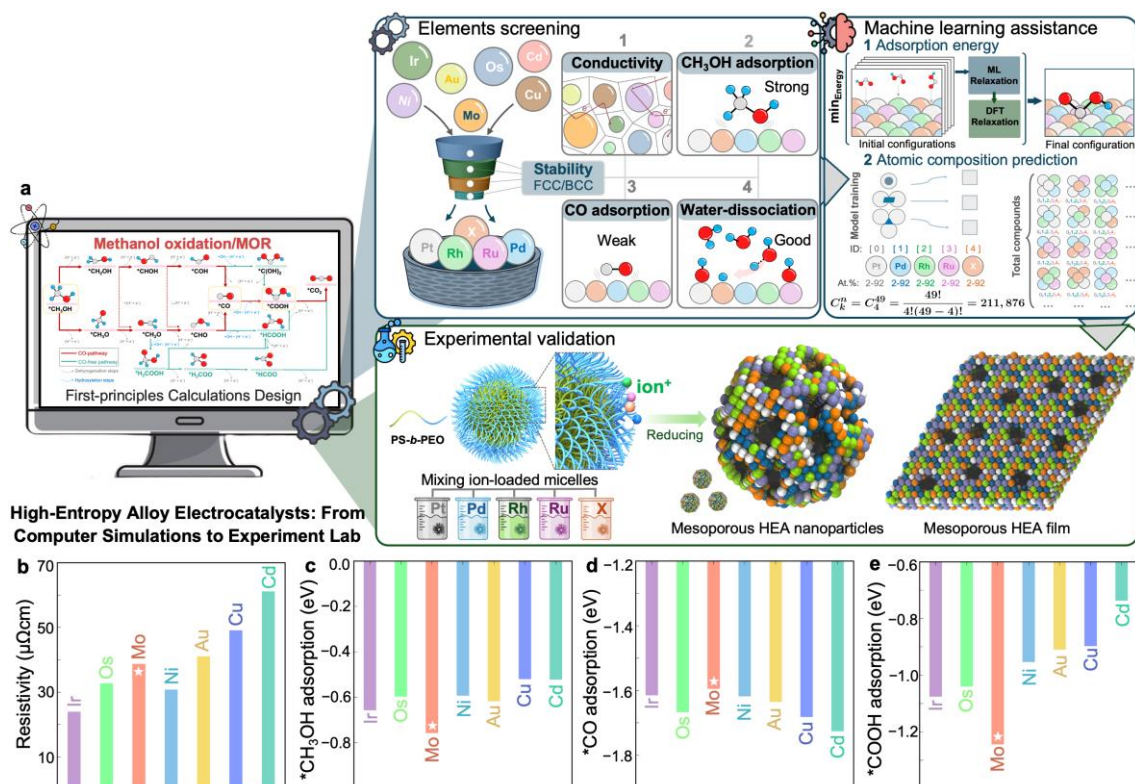


Figure 1. Designing process of potential HEA electrocatalysts for MOR. **(a)** Schematic illustration of designing quinary HEA-PtPdRhRuX for superior electrocatalysis, leveraging machine learning-assisted theoretical predictions to experimental validations. **(b-e)** Computational screening on promising HEA electrocatalysts for the MOR using descriptors of catalyst's electrical resistivity **(b)**, Gibbs free energy of key adsorbates: **(c)** CH_3OH , **(d)** CO , and **(e)** COOH on PtPdRhRuX surface (X = Ir, Os, Mo, Ni, Au, Cu, and Cd).

We initiated the design process by systematically screening the fifth element (X) in the quinary alloy PtPdRhRuX, taking into account potential candidates such as Ir, Os, Au, Cu, Ni, Mo, and Cd. The first step was to determine whether these alloys could form stable solid solutions. Based on valence electron concentration (VEC) analysis¹⁸, the combination of these elements with the four PGMs supports the formation of single-phase solid solutions with an fcc structure ($\text{VEC} > 8$, **Figure S2**). This was further confirmed by calculated phase formation energies, which indicate a strong preference for fcc structure formation thermodynamically over body-centered cubic (bcc) for all seven HEAs (**Figure S2**). Furthermore, the stability of single-phase solid solutions in HEAs is facilitated by small atomic radius differences (δ) among the constituent metals and a sufficiently large ratio of configurational mixing entropy to mixing enthalpy (Ω). As shown in **Figure S3**, the calculated δ and Ω values of the seven HEAs configurations fall well within the critical conditions of $\Omega \geq 1.1$ and $\delta \leq 8.5\%$ ^{18,19}. This suggests a high probability of forming a single-phase solid solution for all HEA candidates. Having verified the stability, the catalytic activity of prospective HEAs was considered. Identifying optimal mechanisms and the best HEA electrocatalyst for MOR is a challenging task due to the wide range of possible intermediates. It is well accepted that methanol oxidation involves six

electron transfer steps and follows a dual-pathway mechanism (**Figure S1**), where the CO-pathway is considered more energetically favorable^{2-4,20,21}. Therefore, during the screening stage, only reactions proceeding via the CO-pathway were evaluated (detailed reaction pathways are illustrated in **Figure S4**, **Table S1**). In order to select a suitable HEA candidate, we defined key criteria for achieving optimal MOR performance: (i) sufficiently low electrical resistivity to facilitate the charge transfer process between the catalyst's active sites and reactants; (ii) strong adsorption capability for CH₃OH to ensure effective reaction progression; (iii) high resistance to CO poisoning to maintain long-term durability; and (iv) excellent water-dissociation ability to accelerate the oxidation reactions rate. In **Figure 1b-e**, the MOR activity of all HEA candidates based on those criteria was collected.

Previous reports have indicated that the poor conductivity of catalysts can limit their electrocatalytic activity^{22,23}. A low enough electrical resistivity, therefore, is crucial to favor efficient electron transfer and enhance overall catalytic efficiency. We found that incorporating elements like Cd, Au, or Cu into the HEA increased electrical resistivity due to the significant reduction of electron lifetimes, driven by strong impurity scattering effects occurring near the Fermi level (**Figure S5**). In contrast, alloying with elements such as Ir, Os, Ni, or Mo resulted in lower resistivity, suggesting these combinations could be more favorable for electrocatalysis (**Figure 1b**). Furthermore, in real reaction environments, water and byproducts can compete with methanol for adsorption on the active sites. A catalyst with a strong affinity for methanol ensures selective adsorption, maintaining a high local concentration of methanol and facilitating efficient oxidation. Accordingly, Mo-based HEA demonstrates significantly more negative free energy of CH₃OH adsorption compared to other elements (by 0.1-0.2 eV, **Figure 1c**). However, what truly sets Mo apart is its exceptional resistance to CO poisoning. Specifically, Mo-based systems exhibit the weakest adsorption tendency for CO intermediates among the investigated HEAs, with an adsorption free energy of -1.6 eV (**Figure 1d**). On the other hand, its adsorption of COOH intermediates is significantly stronger than that of the other HEAs, with an adsorption free energy of at least -1.2 eV, compared to -0.75 eV on the Cd-based HEA and -1.1 eV on the Ir-based system (**Figure 1e**). This trend suggests that CO hydroxylation to COOH on the Mo-based HEA is highly efficient, effectively preventing CO accumulation and ensuring sustained catalytic activity. By taking all these factors into account, we eventually identified the HEA-PtPdRhRuMo compound as the most suitable quinary alloy for the methanol oxidation application.

Unveiling efficient catalytic mechanism and elemental roles of PtPdRhRuMo

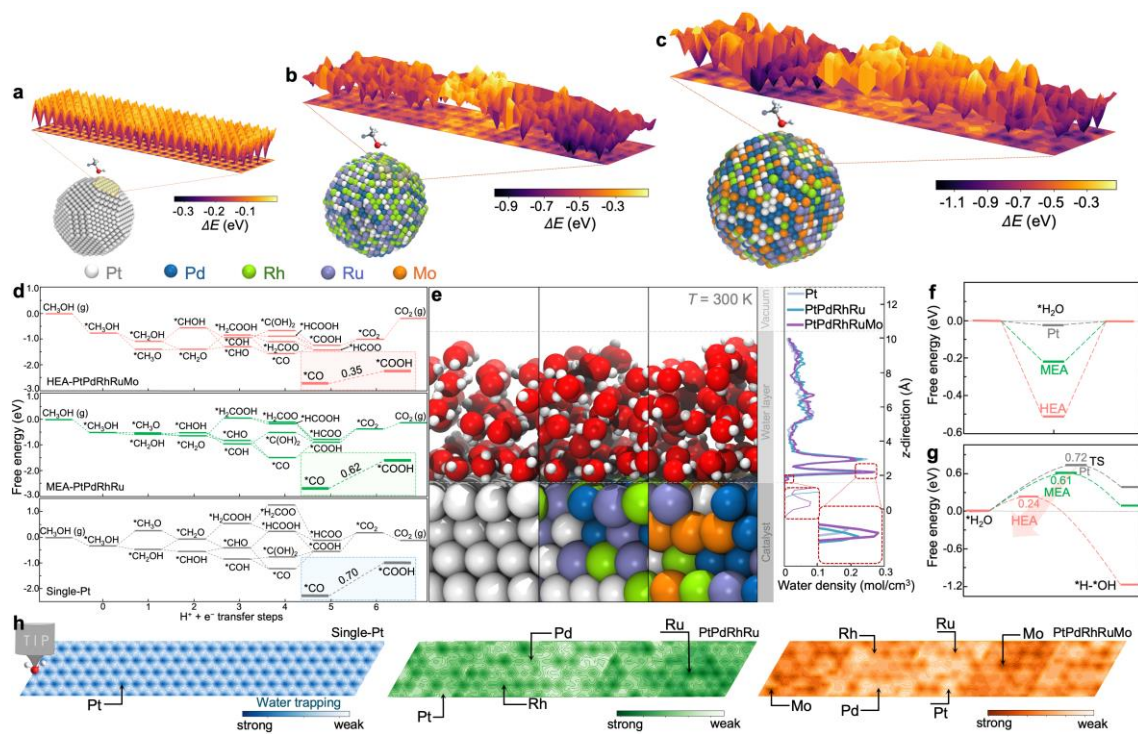


Figure 2. DFT Modelling of the MOR process on three Pt-based catalysts. **(a-c)** Potential energy landscapes for methanol adsorption on **(a)** single Pt(111), **(b)** MEA-PtPdRhRu(111), and **(c)** HEA-PtPdRhRuMo(111) surfaces (random area of 5.5 nm²), where the energy difference (ΔE) referred to maximum energy points. **(d)** Gibbs free energy diagrams of all possible pathways on these catalyst surfaces, with the * denoting adsorbed species. **(e)** Snapshot at 9 ps from AIMD simulations and water density profile along the z-axis, showing the interaction of water with catalysts in the interfacial region at room temperature. Water molecule positions are represented by oxygen atom coordinates. The zero point in the z-axis corresponds to the average of the nuclear position of the top surface atoms. The bulk water concentration is 0.056 mol/cm³. **(f)** Free energy diagram of water adsorption and **(g)** water dissociation steps on three catalysts. **(h)** Water scanning maps highlighting water trapping centers on the surface of the three Pt-based catalysts.

To explore the catalytic activity of HEA-PtPdRhRuMo and further elucidate the role of the fifth element, Mo, its MOR performance was compared with medium-entropy alloy (MEA) PtPdRhRu and single-Pt catalysts (**Table S2**). **Figure 2a-c** illustrates the potential energy landscapes for methanol adsorption on these surfaces. The single-Pt catalyst surface exhibits a uniform potential energy distribution with a small energy difference (~ 0.3 eV) between preferred and non-preferred adsorption sites (**Figure 2a**). In contrast, the potential energy surface of MEA-PtPdRhRu is more complicated, featuring numerous adsorption sites with varied energy minima distributed across the surface (**Figure 2b**). Here, the energy differences at preferred adsorption sites can reach ~ 0.9 eV, indicating an enhanced likelihood of methanol being attracted and trapped in these regions. Likewise, the HEA system not only presents diverse adsorption sites, but its surface also offers the most favorable adsorption centers, with an energy difference of approximately 1.1 eV relative

to other sites (**Figure 2c**). This finding is further supported by the Gibbs free energy diagrams of MOR pathways, as shown in **Figure 2d**. Methanol capturing ability increases significantly in the order Pt < MEA < HEA, with average adsorption free energies of -0.32 eV, -0.52 eV, and -0.76 eV, respectively. This tendency even persists through subsequent dehydrogenation steps, including both C-H [$^*\text{CH}_3\text{OH} \rightarrow ^*\text{CH}_2\text{OH} + (\text{H}^+ + \text{e}^-) \rightarrow ^*\text{CHOH} + 2(\text{H}^+ + \text{e}^-) \rightarrow ^*\text{COH} + 3(\text{H}^+ + \text{e}^-)$] and O-H [$^*\text{CH}_3\text{OH} \rightarrow ^*\text{CH}_3\text{O} + (\text{H}^+ + \text{e}^-) \rightarrow ^*\text{CH}_2\text{O} + 2(\text{H}^+ + \text{e}^-) \rightarrow ^*\text{CHO} + 3(\text{H}^+ + \text{e}^-)$] bond scission pathways. The HEA surface demonstrates superior catalytic activity with the most negative free energies. The significant energy differences between adsorption sites may stem from surface charge redistribution among atoms (**Figure S6**). In MEA, valence electrons are drawn toward more electronegative elements like Pt and Pd (electron acceptors), forming electron-deficient regions on Rh and especially Ru (electron donors). On the HEA surface, charge accumulation around Pt, Pd, and Rh increases significantly, while Mo, due to its lowest electronegativity, serves as the primary electron donor, followed by Ru. Beyond oxophilicity, the substantial electron-deficient regions on these atoms readily accept electrons from adsorbates (thereby attracting them), stabilizing the surface by filling empty orbitals.

The crucial mechanistic step controlling the overall MOR performance efficiency is believed to be related to $^*\text{CO}$. Across all surfaces, we found that $^*\text{CO}$ adsorbates indeed have the lowest free energy among the intermediates, indicating their pronounced stability and the inevitable risk of $^*\text{CO}$ poisoning. This underscores the importance of designing catalysts with either weak CO binding or a strong ability to resolve $^*\text{CO}$ to ensure efficient MOR activity. On the Pt surface, however, the depoisoning process is poorly performed. The hydroxylation step of $^*\text{CO} + \text{OH} \rightarrow ^*\text{COOH}$ is strongly endergonic ($\Delta G = 0.7$ eV), indicating its high susceptibility to CO poisoning, as reported in previous experiments^{3,4,11,20,21}. Notably, the free energy difference of this step becomes smaller on the MEA surface ($\Delta G = 0.62$ eV) while reaching its minimum value on the HEA surface ($\Delta G = 0.35$ eV), revealing a great enhancement of $^*\text{CO}$ hydroxylation. This should be related to the ability of the catalyst surface to adsorb water. The greater the attraction of H_2O molecules to the catalyst surface, the more $^*\text{OH}$ species are likely generated to react with $^*\text{CO}$, which facilitates the oxidation process. To clarify this, *Ab Initio* Molecular Dynamics (AIMD) simulations at room temperature were conducted to investigate interactions between the catalyst surfaces and the water adlayer. In **Figure 2e**, we presented the water density profile along the z-axis, averaged over nine ns of AIMD simulations at room temperature. On the Pt(111) surface, the profile aligns well with previous studies^{24,25}, with two sharp peaks at around 2.25 and 2.95 Å from the surface. On the MEA and HEA surfaces, the water density profiles are similar, though both surfaces show a slightly higher water density at the first peak. Furthermore, the profile on the HEA surface displays a minor peak at 1.9 Å, indicating an enhanced affinity of the HEA surface towards water. This observation is corroborated by the more negative adsorption free energy of water on the HEA surface (-0.514 eV), compared to the MEA (-0.215 eV) and Pt (-0.02 eV) surfaces (**Figure 2f**). After adsorption, the water dissociation process ($^*\text{H}_2\text{O} \rightarrow ^*\text{H}-^*\text{OH}$) was also found to be more

thermodynamically and kinetically favorable on the HEA surface (**Figure 2g**). Specifically, on the HEA surface, the reaction is exergonic (of around -1.2 eV) with a low activation free energy barrier of 0.24 eV. In contrast, the reactions on the MEA and Pt surfaces are endergonic, exhibiting significantly higher activation energy of 0.61 and 0.72 eV, respectively. The large reduction in activation free energy on the HEA surface is attributed to the stronger bonding of the *H and *OH species on the HEA surface, as described by the Evans–Polanyi principle. To highlight the active sites responsible for water adsorption, the scanning maps of water on the surfaces were plotted (**Figure 2h**). Unlike the monometallic system where Pt plays multiple roles, Ru atoms are believed to be crucial active centers responsible for water trapping on the MEA surface. Meanwhile, Mo and its vicinity regions to Ru show a strong affinity for water molecules, suggesting their crucial role as the primary activated centers for water adsorption-dissociation on the HEA surface. Furthermore, the superior water dissociation ability of PtPdRhRuMo facilitates methanol oxidation via CO-free pathways. Specifically, alternative routes requiring the accompaniment of OH radicals [i.e., $^*CH_2O + OH \rightarrow ^*H_2COOH$, $^*CHO + OH \rightarrow ^*HCOOH$, and $^*COH + OH \rightarrow ^*C(OH)_2$] exhibit significantly more stability (more negative free energies) on the HEA surface. This is reasonable owing to the oxyphilic nature and multiple oxidation states on Mo^{26} , enabling more efficient CH_3OH oxidation to CO_2 while minimizing CO intermediate formation compared to different Pt-based catalysts.

Machine-learning predictions on optimal compositions

The addition of Mo significantly enhances the system's catalytic activity, though excessive Mo concentration might have adverse effects. Therefore, it is essential to determine the optimal Mo content for maximizing catalytic efficiency. To predict the PtPdRhRuMo HEA compositions that could deliver optimal MOR performance, we employed a machine learning (ML) approach for this processing²⁷. Specifically, we focused on predicting the adsorption energies of two key MOR intermediates, namely *COOH and *CO (see Methods), as functions of Mo concentration. To this end, we constructed datasets consisting of 340, 528, and 208 data points for *CO adsorption at top, bridge, and hollow sites, respectively, along with 608 data points for *COOH adsorption. These dataset sizes should be sufficient to make reliable predictions of adsorption energies, as noted earlier²⁷. **Figure 3a** presents violin plots of the adsorption energy distributions across different sites. Notably, the median adsorption energy for *COOH is approximately -0.22 eV, which is around 0.3 eV more positive than that of *CO . The adsorption energies for both *COOH and *CO at the top sites span a relatively wide range (approximately 1.7 – 1.8 eV), whereas the *CO adsorption energies at the bridge and hollow sites are confined to a narrower range (1.0 – 1.2 eV). To predict adsorption energies, an ML model accounting for the local atomic environment surrounding the adsorption site was employed. The adsorption energy was expressed as a function of elemental coordination, where each adsorption site is described by the number of neighboring atoms of different elements in distinct coordination zones. Further details on the model construction and zone partitioning are provided in the **Methods** section. Pearson correlation analysis between atomic descriptors and adsorption energies revealed that coordination zones

closest to the adsorbate (zones 1 and 2 for *COOH, and zone 1 for *CO) exert the strongest influence on the adsorption energy. Further details on correlation trends are provided in **Figure S9**.

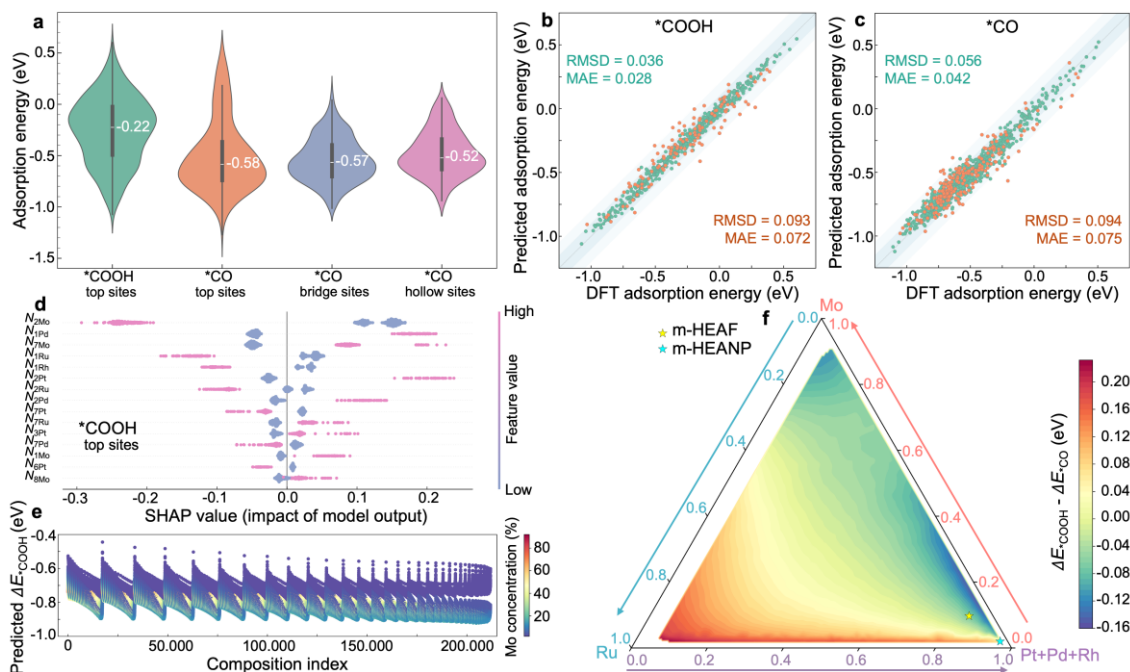


Figure 3. Machine learning prediction on optimal HEA composition. **(a)** Violin plot depicting the distribution of adsorption energy of *COOH and *CO with the median (white tick) values indicated. **(b-c)** Predicted adsorption energies plotted against DFT adsorption energies of **(b)** *COOH (top sites) and **(c)** *CO (top, bridge, and hollow sites) from the CatBoost regression. The training set is shown in green while the test set is shown in orange. The shaded regions (light blue) represent extended values of ± 0.1 and ± 0.2 eV. **(d)** SHAP beeswarm plot showing the impact of the 15 most important descriptors on the predictions of the CatBoost model for the adsorption energy of *COOH. Each point represents a SHAP value (impact on adsorption energy) for a specific descriptor across all data points, whereas color indicates the descriptor value (pink for high and purple for low). The descriptors are ranked by their average absolute SHAP value, with the most impactful features at the top. **(e)** Predicted *COOH adsorption energy of 211,876 possible HEA compositions projected to Mo concentration. **(f)** Pseudo-ternary phase diagram on optimal quinary PtPdRhRuMo compositions (with Pt, Pd, and Rh collected into a single concentration) for CO-depoisoning based on energy difference $\Delta E = \Delta E_{\text{COOH}} - \Delta E_{\text{CO}}$. Star symbols represent experimental HEA samples.

Figure 3b-c depicts the performance of the CatBoost model in predicting *COOH and *CO adsorption energies. It is shown that the model can accurately predict the adsorption energies, with mean absolute error (MAE) of ~ 0.03 and ~ 0.07 eV on the training set and test set, respectively (see also residuals plot showing CatBoost prediction error, **Figure S14**). These results demonstrate that, even with simple descriptors, the model achieved competitive performance compared to those using features from quantum chemistry (QC)

calculations or non-QC features (such as electron count, ionic potential, atomic potential, etc., see also **Figure S8**)^{28–31}. Interestingly, Ridge regression, despite being a linear method, also performed well, achieving MAE values below 0.1 eV on the test sets. The Ridge regression coefficients (**Figure S15**) were also strongly correlated with the Pearson correlation coefficients (**Figure S9**). Analysis of Ridge regression coefficients revealed that Mo atoms coordinating to oxygen in *COOH significantly enhance the adsorption strength. However, this does not automatically imply that a high concentration of Mo will enhance the *COOH adsorption strength because (i) the Ridge model lacks non-linear terms, and (ii) the contribution of Mo in other zones must also be considered. For example, Mo in zone 7, in contrast, decreases the adsorption strength of *COOH. This observation is also supported by SHapley Additive exPlanations (SHAP) analysis on the CatBoost model³², presented in **Figures 3d** and **S16**. The SHAP values also showed that adsorbate-coordinating atoms contribute most significantly to adsorption energy predictions: zones 1 and 2 for *COOH and zone 1 for *CO. Specifically, for *COOH, high N_{2Mo} data points (represented by pink dots) are mostly on the negative side of the SHAP plot, indicating that a high N_{2Mo} value strengthens the binding. On the other hand, the N_{7Mo} descriptor exhibits a negative correlation with *COOH adsorption strength, with a majority of high-value data points being on the positive side of the SHAP plot.

Using the CatBoost model, we then predicted the adsorption energies of *COOH and *CO across 211,876 HEA compositions. **Figures 3e** and **S17** illustrate the impact of Mo concentration on the adsorption energy of *COOH. The data points are densely distributed, covering a wide range of adsorption energies from -0.44 to -0.92 eV. The observed banded pattern suggests systematic variations in adsorption energy depending on composition. We observed that *COOH adsorption is generally weak at very low Mo concentrations (a few percent), strongest at moderate Mo concentrations (10-20%), and slightly weaker at high Mo concentrations (>50%). This trend indicates that Mo plays a non-monotonic role in tuning *COOH adsorption, likely due to the dual interaction of *COOH with the surface via both carbon and oxygen. For *CO, the adsorption energy varies between -1.03 and -0.60 eV (**Figure S18**). CO adsorption is weakest at high Mo concentrations but strongest at low Mo concentrations, highlighting the contrasting role of Mo in stabilizing *COOH versus *CO adsorption. **Figure 3f** displays a pseudo-ternary phase diagram of the COOH-CO adsorption energy difference ($\Delta E = \Delta E_{*COOH} - \Delta E_{*CO}$) as a function of HEA composition, with Pt, Pd, and Rh collected into a single concentration. Corresponding phase diagrams for *COOH and *CO adsorption energies are shown in **Figures S19** and **S20**. We use the COOH-CO adsorption energy difference to evaluate HEA performance based on the idea that a surface capable of stabilizing *COOH relative to *CO (blue/green areas) can promote water dissociation and mitigate *CO poisoning. Remarkably, the optimal compositions, where this gap is minimized, span a broad range of Mo concentrations but consistently feature low Ru content. The composition with the smallest COOH-CO gap is found to be 16% Mo, with Pt, Pd, Rh, and Ru concentrations of 66%, 2%, 14%, and 2%, respectively. Notably, this composition closely aligns with the one minimizing *COOH adsorption energy (56% Pt, 2% Pd, 24% Rh, 2% Ru, and 16% Mo; **Figure S19**). The optimal composition is rich in Pt, Pd, and Rh, all of which have an fcc crystal structure and relatively low

(111) surface energies (2.0–2.7 J/m²)³³, which favor the formation of a single-phase solid solution (*vide supra*). Meanwhile, the combined Mo (bcc) and Ru (hcp) content remains around 18%, ensuring a balance between stability and catalytic activity. Finally, we note that while the optimal compositions identified in **Figure 3f** are expected to be *CO-tolerant, they may not necessarily yield the highest overall MOR performance. Future optimization should incorporate other crucial factors, such as C–H activation in methanol and contributions from *CO-free pathways, which were beyond the scope of this ML-driven study.

Synthesis and electrochemical performance of PtPdRhRuMo

Mo-based HEA catalysts were eventually synthesized and electrochemically tested to validate theoretical predictions regarding their catalytic performance. To highlight the beneficial effect of Mo incorporation, mesoporous HEA-PtPdRhRuMo nanoparticles [namely, m-HEANP(Mo)] were designed along with various nanostructures for comparison, including mesoporous HEA-PtPdRhRuIr [m-HEANP(Ir)], mesoporous HEA-PtPdRhRuAu [m-HEANP(Au)], mesoporous HEA-PtPdRhRuNi [m-HEANP(Ni)], and mesoporous MEA-PtPdRhRu (m-MEANP) (see **Figure 4** and **Figure S21**). The co-polymer micelle-assisted soft-templating approach in combination with wet chemical synthesis methodology is used for porosity institution (see **Methods** and SI). In **Figure 4a-b**, the scanning electron microscopy (SEM) and high-angle annular dark-field (HAADF) scanning transmission electron microscopy (HAADF-STEM) images reveal the mesoporous features in m-HEANP(Mo) nanoparticles. Additionally, the energy dispersive spectroscopy (EDS) in HAADF-STEM mode is used to visualize the elemental distribution profile in the m-HEANP(Mo) system, confirming the uniform distribution of constituent Pt, Pd, Ru, Rh, and Mo elements in the structure (**Figure 4c-d**, **Table S4**). Along with the elemental atomic content obtained from SEM-EDS analysis (**Figure S22**), the atomic ratio of Pt/Pd/Rh/Ru/Mo in m-HEANP(Mo) was determined to be 59/17/20/2/2 by inductively coupled plasma optical emission spectroscopy (ICP-OES, **Table S5**), suggesting that this multi-elemental nanostructure is stabilized with a mixing entropy configuration of $\Delta S_{\text{mix}} \sim 1.1R^{12,34}$. The multi-elemental character of the m-HEANP(Mo) exterior is also evident from the intense characteristic peaks of Pt, Pd, Ru, Rh, and Mo in the wide-scan X-ray photoelectron spectroscopy (XPS) spectrum (**Figure S23a**), highlighting its high entropic feature.

To further confirm the high-entropy effect in m-HEANP(Mo), the valence band (VB) spectrum was examined using hard X-ray photoelectron spectroscopy (HAXPES, Cr K α source) (**Figure 4f**). Accordingly, the featureless VB spectrum of m-HEANP(Mo), in contrast to the monometallic Pt system, reflects entropy-driven modifications in the overall electronic structure³⁵. Moreover, the powder X-ray diffraction (XRD) pattern exhibits characteristic peaks identical to those of the Pt-system (JCPDS card No. 03-065-2868), confirming that the m-HEANP(Mo) nanoparticles crystallize in a single-phase fcc structure (**Figure 4e**). The lattice constant determined from the XRD pattern was 0.392 nm, which is comparatively larger than that of its constituent elements: Rh (0.380 nm), Mo (0.314 nm), Ru (0.271 nm), Pd (0.385 nm), and Pt (0.391 nm).

This lattice distortion can be attributed to entropy-driven phase purity, resulting from multiple atomic species with different sizes residing in one unit cell³⁶.

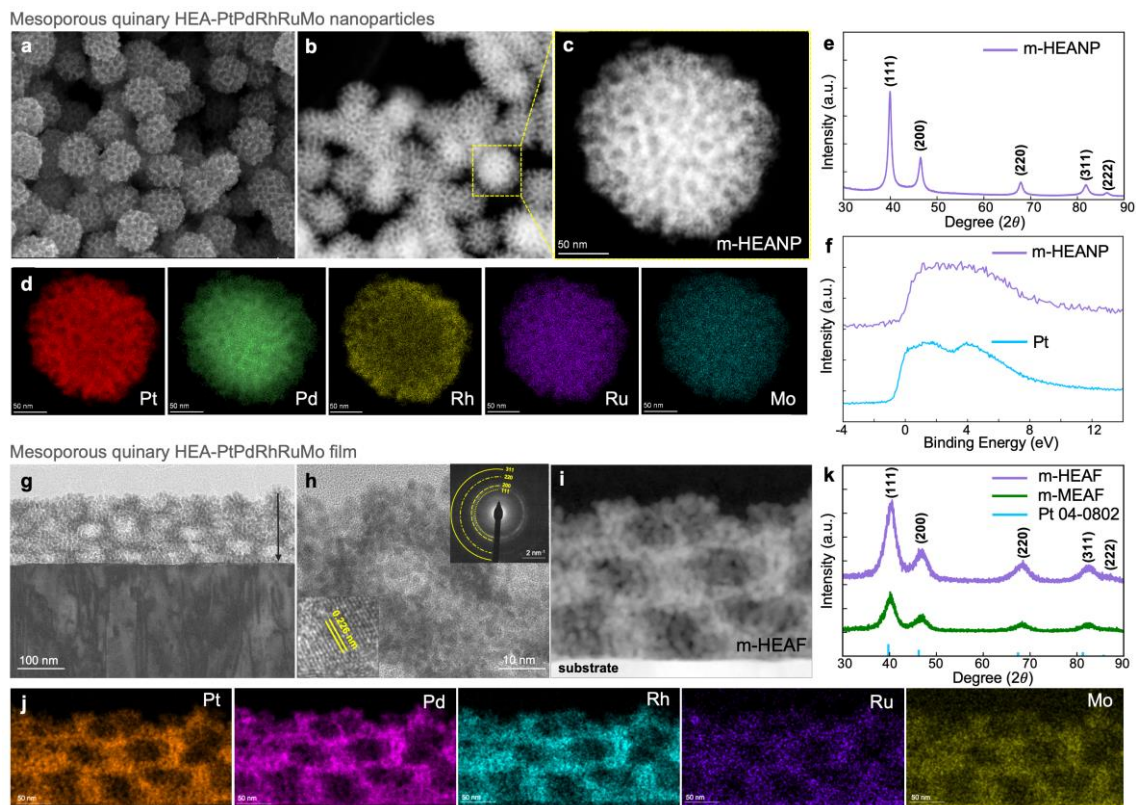


Figure 4. Synthesis of mesoporous quinary PtPdRhRuMo catalysts. (a) SEM and (b) HAADF-STEM images of mesoporous HEA-PtPdRhRuMo nanoparticles (m-HEANP). (c) HAADF-STEM image of a nanoparticle subjected to EDS mapping and (d) associated elemental distribution profiles of Pt, Pd, Ru, Rh, and Mo, respectively. (e) Powder XRD pattern of m-HEANP and (f) the valence band spectra of m-HEANP and Pt. (g) TEM and (h) HRTEM images of mesoporous HEA-PtPdRhRuMo film (m-HEAF), with inset SAED pattern. (i) HAADF-STEM image and (j) the corresponding EDS mapping of all elements in m-HEAF. (k) XRD patterns of m-HEAF and m-MEAF referred to Pt-system (JCPDS: 04-0802).

It should be noted that the critical threshold defining high-entropy alloys has recently evolved^{34,37} (details of its definition(s) are presented in SI), shifting the research focus from creating ideal alloys that strictly adhere to the entropy criterion to regulating entropy as a tool for tailoring compositions and achieving desired material properties³⁴. Nevertheless, HEA samples with higher mixing entropy configurations have also been considered. Mesoporous quinary HEA-PtPdRhRuMo film [m-HEAF(Mo)] and mesoporous MEA-PtPdRhRu film (m-MEAF) were then synthesized through soft-templated electrochemical deposition. The fabrication process employed a polished Au-Ti-Si working electrode immersed in a micellar electrolyte containing copolymers and multimetallic precursors. The cross-sectional TEM analysis of focused ion beam (FIB)-prepared specimens revealed mesoporous structural integrity throughout the m-HEAF(Mo) (**Figure 4g**).

High-resolution transmission electron microscopy (HRTEM) showed lattice fringes with an interplanar spacing of 0.226 nm, corresponding to the (111) plane of the fcc structure (**Figure 4h**). In addition, the HAADF-STEM imaging confirmed the three-dimensional continuity of the mesochannels (**Figure 4i**). Furthermore, elemental homogeneity was verified through STEM-EDS mapping, with line-scan profiles demonstrating spatial uniformity of all constituent metals (Pt, Pd, Rh, Ru, Mo) across the mesoporous film (**Figure 4j**). The atomic ratio of Pt/Pd/Rh/Ru/Mo was also determined to be 30/37/17/7.7/8.3 by ICP-OES, corresponding to ΔS_{mix} value of 1.4*R*. The XRD analysis of both the m-MEAF and m-HEAF(Mo) samples exhibited distinct characteristic peaks corresponding to the fcc structure of Pt, consistent with mesoporous alloy nanoparticles (**Figure 4k**). Compared to m-MEAF, the diffraction peaks of the m-HEAF(Mo) shift toward higher angles, indicating lattice shrinkage due to the incorporation of smaller Mo atoms, further illustrating its alloy nature. These samples have reasonable atomic components within the optimal range for the MOR reaction, as suggested by the theoretical calculations. On the other hand, high-resolution XPS (HRXPS, **Figure S23b**) analysis on the Pt 4*f* core levels of both the m-HEAF(Mo) and m-HEANP(Mo) samples indicates a noticeable negative shift in the Pt 4*f* binding energy of both m-HEAF(Mo) and m-HEANP(Mo) compared to Pt-C. These results indicate a more electron-rich Pt environment owing to inter-element charge transfer from more electropositive elements, such as Mo. The shift is more pronounced in m-HEAF(Mo) sample compared to that in m-HEANP(Mo), which correlates well with its higher Mo content. This changed electron density could modulate the *d*-band structure of Pt, weakening the adsorption of poisoning intermediates and thereby contributing to its enhanced MOR performance.

To evaluate the electrochemical performance of the proposed PtPdRhRuMo alloy systems, catalyst samples were subjected to the methanol electro-oxidation reaction (MOR) in an alkaline medium (**Figure 5**). Their MOR activity was evaluated using a typical three-electrode system and an electrolyte solution of 1.0 M KOH + 1.0 M methanol. Before the MOR test, all the prepared working electrodes were electrochemically cleaned in nitrogen-saturated 1.0 M KOH solution. For comparison, the m-HEANP(Ir), m-HEANP(Au), m-HEANP(Ni), and m-MEANP were also prepared in the same condition, alongside commercially available Pt-C (20 wt. % Pt loading) (see SI). Characteristic hydrogen adsorption-desorption behavior (**Figure S24**) observed within the potential window of 0.06–0.40 V vs RHE indicates high Pt atom utilization across all HEA systems. The electrochemical active surface area (ECSA) of the electrocatalysts in this study was determined via hydrogen under potential deposition (**Table S6**). In **Figures 5a and S25**, clear anodic peaks during forward and backward scans indicate the electrooxidation of methanol and its intermediates in MOR studies for all electrocatalysts³⁸. Notably, m-HEANP(Mo) demonstrates significantly higher MOR activity (12.02 mA/cm²), outperforming m-HEANP(Ir) (7.92 mA/cm²), m-HEANP(Au) (0.33 mA/cm²), m-HEANP(Ni) (0.39 mA/cm²), m-MEANP (6.11 mA/cm²), and commercial Pt-C (2.04 mA/cm²). This result highlights the effective role of Mo as the fifth element in the PtPdRhRu system, enhancing the MOR process in alignment with our previous theoretical predictions. This enhancement is further supported by the lowest onset potential observed for the Mo-based HEA system ($E_{\text{onset}} \sim 0.446$ V) compared to the other catalysts (**Figure 5b**), indicating more facile

methanol adsorption and a lower MOR activation barrier on m-HEANP(Mo)³⁹. In addition, the mass activity (MA) of m-HEANP(Mo) was estimated at 7.70 A mg_{Pt}⁻¹ and 3.55 A mg_{all-metals}⁻¹, which is considerably higher than that of m-HEANP(Ir) (2.67 A mg_{Pt}⁻¹ and 1.33 A mg_{all-metals}⁻¹), m-HEANP(Au) (0.55 A mg_{Pt}⁻¹ and 0.17 A mg_{all-metals}⁻¹), m-HEANP(Ni) (0.53 A mg_{Pt}⁻¹ and 0.18 A mg_{all-metals}⁻¹), m-MEANP (1.92 A mg_{Pt}⁻¹ and 0.97 A mg_{all-metals}⁻¹), and commercial Pt-C (0.68 A mg_{Pt}⁻¹ and 0.68 A mg_{all-metals}⁻¹) (see **Figure 5c,g**). To shed light on MOR durability, the chronoamperometry (CA) test was investigated at 0.640 V vs RHE for these catalysts throughout 10,000 s. As shown in **Figure 5d**, m-HEANP(Mo) exhibits high MOR activity and long-term durability, retaining 2.57 A mg_{Pt}⁻¹ after 10,000 s (approximately 48% of its initial activity, MA_{@t0} = 5.35 A mg_{Pt}⁻¹ at *t* = 0). This performance remarkably surpasses that of m-HEANP(Ir), which retains only ~11% of its initial activity (MA_{@t0} = 2.42 A mg_{Pt}⁻¹ and MA_{@t10000} = 0.27 A mg_{Pt}⁻¹); m-HEANP(Au) with ~40% (MA_{@t0} = 0.76 A mg_{Pt}⁻¹ and MA_{@t10000} = 0.30 A mg_{Pt}⁻¹); m-MEANP with ~27% (MA_{@t0} = 0.17 A mg_{Pt}⁻¹ and MA_{@t10000} = 0.05 A mg_{Pt}⁻¹); and Pt-C with ~16% (MA_{@t0} = 0.14 A mg_{Pt}⁻¹ and MA_{@t10000} = 0.02 A mg_{Pt}⁻¹). Notably, m-HEANP(Ni) exhibits good stability with comparable retention of ~51% (MA_{@t0} = 0.99 A mg_{Pt}⁻¹ and MA_{@t10000} = 0.50 A mg_{Pt}⁻¹). Moreover, the extended CA test was also carried out on m-HEANP(Mo) to test its long-term durability. The MOR activity of our catalyst was restored by replacing a fresh electrolyte solution after every 10,000 s for 10 consecutive cycles of the CA test (**Figure 5e**), suggesting appreciable reproducibility of the catalytic activity. These results suggest that the Mo-based HEA system is indeed a suitable electrocatalyst for effective MOR performance.

A similar trend was observed in the film samples, where the incorporation of Mo as the fifth element in the m-MEAF resulted in a noticeable improvement in both onset potential (**Figure S26**) and MOR activity (**Figure 5f**). This again suggests the facile adsorption of methanol molecules and their effective oxidation on m-HEAF(Mo)³⁹. In particular, the m-HEAF(Mo) exhibits the highest MOR-specific activity of 18.20 mA/cm², which is ~1.5 times higher than the m-MEAF (12.28 mA/cm²) and 8.3 times greater than commercial Pt-C (2.2 mA/cm²). Besides, m-HEA film has a larger forward (*I_f*) to backward (*I_b*) MOR current ratio (*I_f*/*I_b* ~ 3.87) than m-MEAF (~3.46), suggesting better handling of reaction intermediates^{38,39} on HEA film, consistent with the computational predictions. Among the considered catalysts, m-HEAF(Mo) delivers the highest MOR activity for both Pt-mass loading and all-metals-mass loading, which is 9.89 A mg_{Pt}⁻¹ and 4.49 A mg_{all-metals}⁻¹, respectively (**Figures 5g, S27, and Table S7-S8**). Moreover, the significant enhancement in MOR activity (for both specific current and mass activity) of Mo-based HEA catalysts surpasses many recently reported Pt-based catalytic systems and HEA systems (**Figure 5h and Table S8**). Further analysis on electrochemical impedance spectroscopy (EIS) (**Figure S28**) and Randles–Ševčík (*R*–*S*) relationship (**Figure S29**) also reveals that the superior MOR performance of PtPdRhRuMo originates from a synergistic combination of enhanced intrinsic activity (compositional complexity transitioned from medium to high entropy) and porosity integration (optimized mass transport).

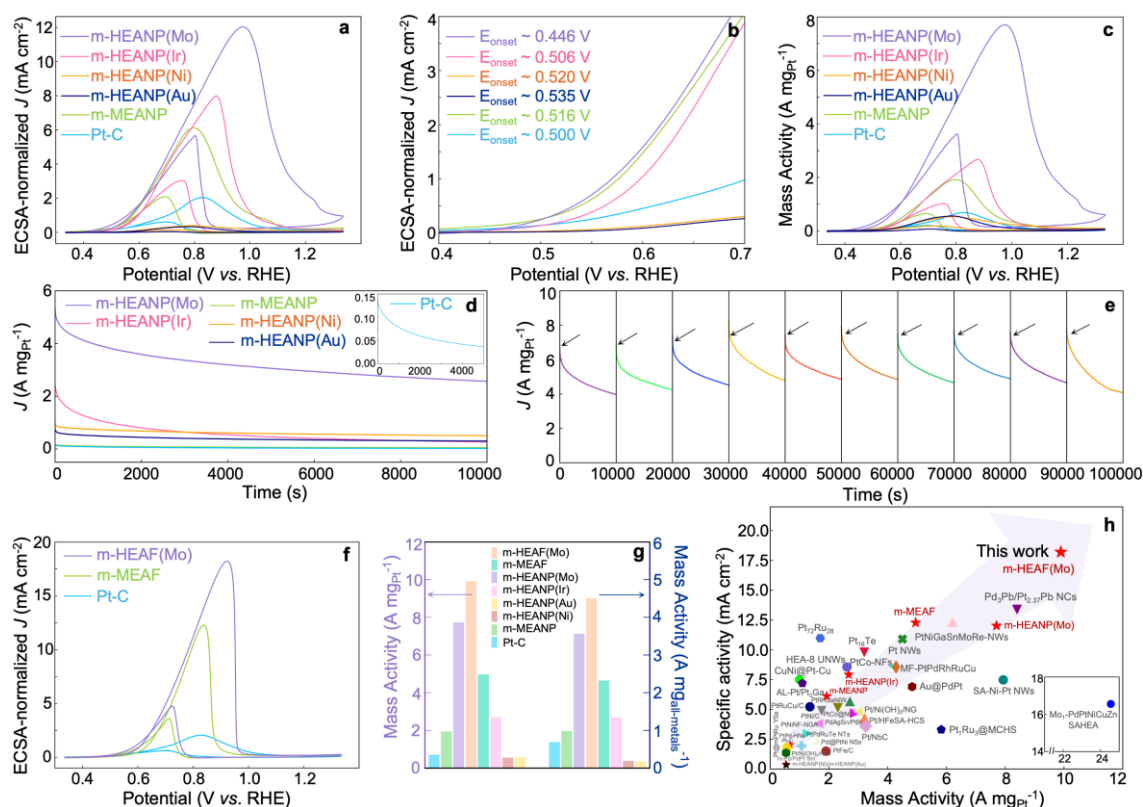


Figure 5. MOR performance of quinary HEA-PtPdRhRuMo. (a) ECSA-normalized CV profiles of m-HEANP(Mo), m-HEANP(Ir), m-HEANP(Ni), m-HEANP(Au), m-MEANP, Pt-C, and (b) their corresponding onset potential from forward scan in the potential window of 0.40 to 0.75 V in an electrolytic solution of 1.0 M KOH : 1.0 M CH₃OH using potential scan rate of 50 mV s⁻¹. (c) MOR mass activities concerning Pt loading of m-HEANP(Mo), m-HEANP(Ir), m-HEANP(Au), m-HEANP(Ni), m-MEANP, and commercial Pt-C. (d) Chronoamperometric (CA) tests at 0.640 V vs RHE on Pt-C, m-MEANP, m-HEANP(Ir), m-HEANP(Au), m-HEANP(Ni), and m-HEANP(Mo). The inset shows the magnified CA profile of Pt-C for the first 4000 s. (e) Long-term CA durability test of mesoporous HEA-PtPdRhRuMo, where the arrows indicate when the electrolyte is changed. (f) ECSA-normalized CV profiles of m-HEAF(Mo), m-MEAF, and Pt-C. (g) Mass activities concerning Pt-loading and all-metals loading of Pt-C, m-MEANP, m-HEANP(Ir), m-HEANP(Mo), m-MEAF, and m-HEAF(Mo). (h) The comparative specific MOR activity and mass activity (Pt-loading) of m-HEAF(Mo), m-MEAF, m-HEANP(Mo), m-HEANP(Ir), m-HEANP(Ni), m-HEANP(Au), and m-MEANP with the recently reported HEAs and Pt group metals-based electrocatalysts (tabulated in the MOR comparative Table S8).

Eventually, to further elaborate on the enhanced CO-poisoning resistance and shed some light on reaction intermediates during MOR electrocatalysis, we employed in-situ Attenuated Total Reflectance Surface-Enhanced Infrared Absorption Spectroscopy (ATR-SEIRAS) and CO stripping voltammetry on m-HEANP(Mo) and commercial Pt-C catalysts for comparison (**Figures 6 and S30**). Several characteristic infrared bands associated with MOR intermediates were observed in the 2500-1000 cm⁻¹ range across the

investigated potential window. Specifically, a downward band at $\sim 2340\text{ cm}^{-1}$ corresponds to CO_2 (asymmetric O–C–O stretching vibration, ν_{as})^{40,41}, indicating the final product of complete methanol oxidation. Bipolar bands near $\sim 2040\text{ cm}^{-1}$ are attributed to linearly adsorbed CO species^{42–46}, while a peak at $\sim 1700\text{ cm}^{-1}$ is assigned to the carboxylic species ($-\text{COOH}$)^{47–49}. Distinct downward peaks at ~ 1570 , ~ 1350 , ~ 1200 , and $\sim 1100\text{ cm}^{-1}$ are ascribed to formate ions HCOO^- ($\nu_{\text{as}}(\text{O–C–O})$ and $\delta(\text{C–H})$ vibrations) and its overlapping signals with carbonate ions (CO_3^{2-}) and methoxyl species ($-\text{OCH}_3$), respectively^{50–54}. Additionally, bands at $\sim 1030\text{ cm}^{-1}$ are attributed to CH_3OH adsorption via $\nu(\text{C–O})$ stretching⁵⁵, and bands at $\sim 1450\text{ cm}^{-1}$ originate from $\text{CO}_3^{2-}/\text{HCO}_3^-$ species formed by the reaction between OH^- and desorbed CO_2 ⁵⁰.

As shown in **Figure 6a-b**, CO_2 peaks appear at a much lower potential (0.40 V) on PtPdRhRuMo compared to Pt-C (0.55 V), indicating more facile complete oxidation of methanol. Notably, while CO adsorption peaks ($\sim 2040\text{ cm}^{-1}$) are present across the entire applied potential range with significant intensity on Pt-C, their appearance on PtPdRhRuMo is limited to a narrow low-potential window (0.25–0.45 V) with only small intensity, and they quickly disappear at higher potentials. This behavior highlights the remarkable CO-poisoning tolerance and faster oxidation kinetics on the PtPdRhRuMo surface. Indeed, CO-stripping voltammetry results in **Figure 6c-d** further confirm the superior CO-tolerance of PtPdRhRuMo. Compared to the commercial Pt-C catalyst, which exhibits a CO oxidation peak (E_p) of 0.759 V and an onset oxidation potential (E_{onset}) of 0.603 V, PtPdRhRuMo shows negatively shifted values of $E_p = 0.686\text{ V}$ and $E_{\text{onset}} = 0.590\text{ V}$. These shifts indicate weaker CO binding strength and improved CO tolerance⁴⁶, which are advantageous for methanol oxidation, consistent with our theoretical predictions.

Furthermore, the adsorption bands of methoxyl and carboxylic species on PtPdRhRuMo are significantly enhanced than those on Pt-C, suggesting more effective activation of methanol and key intermediates. Strong downward peaks associated with carboxylic species and especially formate ions, products of the CO-free pathways, are also more prominent on PtPdRhRuMo, revealing that alternative reaction routes beyond the CO-pathway are favored and enhanced. Combining evidence from in-situ ATR-SEIRAS, CO-stripping curves, and electrochemical tests, we demonstrated that PtPdRhRuMo is a highly promising HEA catalyst with superior catalytic performance and high CO-poisoning resistance. These findings confirm the effectiveness of theoretical calculations in guiding the rational design of catalysts for MOR applications.

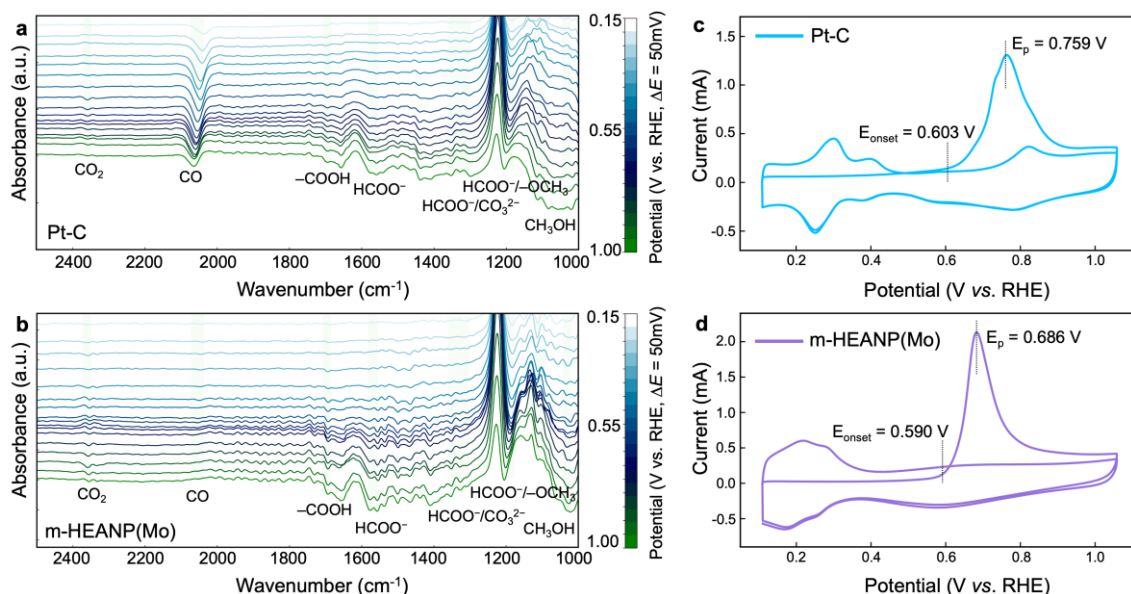


Figure 6. In-situ ATR-SEIRAS spectra and CO-stripping curves analysis of different catalysts. (a) In-situ ATR-SEIRAS spectra by internal reflection mode of commercial Pt-C and (b) m-HEANP(Mo) catalysts. All spectra were recorded from 0.15 to 1.00 V vs. RHE in 1.0 M KOH : 1.0 M CH₃OH solution. (c-d) CO-stripping voltammograms of (c) commercial Pt-C and (d) m-HEANP(Mo) catalysts.

Conclusions

In summary, we reported an effective bottom-up approach in developing high-performance high-entropy alloy electrocatalysts for methanol oxidation reactions. Accordingly, quinary PtPdRhRuMo catalysts indeed demonstrate the desired physicochemical properties to promote efficient methanol oxidation, including strong affinity to CH₃OH, low electrical resistivity, high resistance to CO poisoning, and great water-dissociation ability. Besides its superior performance, the use of precious metals or the difficulty in precisely controlling the atomic composition is considered an existing limitation. Nevertheless, within the scope of this work, the comprehensive integration of first-principles calculations, machine learning, and experimental validation has proven to be an effective strategy for accelerating the design of this class of materials with impressive performance. This suggests strong potential for advancing high-performance catalytic materials not only for methanol oxidation but also for a range of electrochemical reactions (such as oxygen reduction reaction, hydrogen oxidation reactions, etc). Moreover, it potentially paves the way for future research with more abundant and cost-effective metals while maintaining high catalytic activity for applications in energy conversion and beyond.

Methods

First-principles calculations

DFT calculations were performed using the Vienna Ab *initio* Simulation Package⁵⁶ (VASP) with a plane-wave basis set

and an energy cutoff of 450 eV. The projector-augmented wave (PAW) method⁵⁷ was used to describe core electrons, while the revised Perdew-Burke-Ernzerhof (RPBE) functional⁵⁸ accounted for exchange-correlation parts. The irreducible Brillouin zone was sampled using a Γ -centered $2'2'1$ k -point mesh along with a Gaussian smearing width of 0.2 eV and an energy convergence threshold of 10^{-4} eV. Grimme's D3 van der Waals (vdW) correction⁵⁹ was applied to account for weak dispersion forces between adsorbates and the surface. All models were built on a 5×5 unit cell of the (111) facet, consisting of 100 atoms arranged in a four-layer slab. The bottom two layers were fixed to mimic the bulk structure, while the upper layers were fully relaxed until residual forces were below 3×10^{-2} eVÅ⁻¹. Here, all elements in MEA and HEA systems are present in equiatomic compositions. A vacuum region of 15 Å was added along the z -direction for all substrates. To simulate elemental disorder in multimetallic alloys, 1000 random configurations were generated for each alloy, and the five most stable ones in energy were selected to evaluate catalytic activity in average. To analyze the phase formation energy, average electronic structures, and residual resistivity of bulk alloys, a Korringa-Kohn-Rostoker Green's function method combined with the coherent potential approximation^{60,61} (KKR-CPA) was implemented in the AkaiKKR code^{62,63}, using the maximum angular momentum of $l_{\max} = 3$ and an imaginary part of $\eta = 10^{-5}$ Ry.

The Gibbs free energy of each species was then defined as $G = E + ZPE - TS$, where E is the total energy, ZPE is the zero-point energy correction, and S is the vibrational entropy of the adsorbed intermediate^{64,65}. The catalytic activity was estimated using the relative free energy (ΔG) of possible reactions (see SI) at $p = 1$ atm, $\text{pH} = 0$, and $T = 298.15$ K, where $\Delta G = \Delta E + \Delta ZPE - T\Delta S$. For proton-electron transfer steps, the computational hydrogen electrode model was used⁶⁶, where $G(\text{H}^+ + \text{e}^-)$ equals $G(1/2\text{H}_2(\text{g}))$, corresponding to RHE. Solvent effects were also estimated using the implicit solvation model from VASPsol⁶⁷, while the climbing image nudged elastic band (CINEB) method was applied to determine transition-state energy barriers. For AIMD simulations, an initial layer of water with a density of around 1 g/cm³ (43 H₂O molecules) was added on the catalyst surfaces and heated to 300 K over 1.25 ps (timestep = 0.25 fs) using the standard NVT ensemble. The systems were then stabilized at 300 K for 2 ps before diffusion was investigated for over 9 ps.

Machine learning

Given a large number of active sites in alloy systems, a machine learning model trained on large-scale graph neural networks from the Open Catalyst Project^{68,69} was integrated with DFT calculations to accelerate optimization and identify optimal reaction pathways⁷⁰. The adsorption energies of *COOH and *CO were then calculated relative to CH₃OH, using the following equations:

$$\Delta E_{(\text{*COOH})} = [E_{(\text{*COOH})} + 5/2 E_{(\text{H}_2)}] - [E_{(\text{*})} + E_{(\text{CH}_3\text{OH})} + E_{(\text{H}_2\text{O})}]$$

$$\Delta E_{(\text{*CO})} = [E_{(\text{*CO})} + 2E_{(\text{H}_2)}] - [E_{(\text{*})} + E_{(\text{CH}_3\text{OH})}].$$

Four datasets of COOH and CO adsorption on the PtPdRhRuMo HEA were first constructed. We calculated *COOH and *CO adsorption on 30 of the most stable (5×5) HEA surfaces, each with equal atomic percentages of Pt, Pd, Ru, Rh, and Mo (**Table S3**). The Xsorb code⁷¹ was used to systematically generate different configurations. For *COOH, we focused on top-site adsorption, where both the carbon and oxygen atoms are positioned at adjacent top sites, whereas for *CO, we considered all absorption sites, including top, bridge, fcc hollow, and hcp hollow sites. Each surface contains 75 adsorption configurations in total. Since the adsorbate molecules were fully optimized without any constraints, many different initial configurations converged to the same local minimum. Thus, to ensure dataset uniqueness, only distinct

optimized structures were retained in the database. Additionally, to better capture the adsorption of *COOH and *CO on surfaces with a high concentration of one single metal, we extended the dataset with the adsorption of *COOH and *CO on pure-metal fcc surfaces. Machine learning models were constructed to predict the adsorption energies based on the local atomic environment surrounding the adsorption site. For *COOH adsorption, the surface was divided into nine zones, shown in **Figure S7**. The adsorption energy is calculated as $\Delta E_{(*\text{COOH})} = f(N_{1\text{Pt}}, N_{1\text{Pd}}, N_{1\text{Ru}}, N_{1\text{Rh}}, N_{1\text{Mo}}, \dots, N_{9\text{Pt}}, N_{9\text{Pd}}, N_{9\text{Ru}}, N_{9\text{Rh}}, N_{9\text{Mo}})$, where N_{kX} represents the number of atoms of element X in zone k ($k = 1-9$). For *CO adsorption at top sites, we employed a three-zone model, following a similar strategy used for *O adsorption²⁷. For *CO adsorption at bridge and hollow sites, we used a five-zone partitioning to better capture the local coordination effects. Additional descriptors related to atomic physicochemical properties, such as electronegativity, atomic radius, and the number of d-electrons were also considered (**Figure S8**). However, the results indicated that simple descriptors relied on the local atomic environment are sufficient to achieve comparable predictive accuracy. We note that, due to the large supercell employed in this study, we were able to use an extended zone approach without encountering periodic boundary conditions artifacts.

Each dataset was split into training and test sets with a ratio of 80:20. To train the model, we explored several regression techniques, including Ridge regression, Support Vector Regression (SVR), Random Forest Regression, three gradient-boosting algorithms (Gradient Boosting Regression, XGBoost Regression, and CatBoost Regression), and Multi-Layer Perceptron (MLP) Regression. Hyperparameters were optimized using GridSearchCV with a 5-fold cross-validation. We found that most models yielded comparable performance, except for Random Forest Regression, which exhibited strong overfitting (**Figures S9-S13**). Ultimately, we selected CatBoost regression³² for further study due to its strong predictive accuracy, fast prediction speed, and built-in overfitting prevention (**Figure 3b-c** and **Figures S9-S13**). The CatBoost model was used to predict the adsorption of *COOH and *CO on surfaces with different compositions. For each composition, we generated 1000 random 5×5 surfaces. On each surface, the adsorption energies of *COOH and *CO for all possible configurations (50 for *COOH and 150 for *CO) were predicted. We then collected the most stable configuration, i.e., the one with the most negative adsorption energy. The adsorption energy on a configuration is then averaged over 1000 surfaces. In total, $1000 \times (50 + 150) = 200,000$ adsorption energy evaluations were performed per composition. Given the fast prediction of CatBoost, we directly evaluated a large number of possible compositions by changing the composition of each metal from 2% to 92% in 2% increments (resulting in 211,876 possible HEA compositions), instead of relying on optimization techniques such as Genetic Algorithms or Bayesian optimization⁷².

Synthesis of mesoporous HEA samples

Mesoporous PtPdRhRuMo high-entropy alloy nanoparticles [m-HEANP(Mo)] were synthesized via micelle assembly using polystyrene-*b*-poly(ethylene oxide) (PS₅₀₀₀-*b*-PEO₂₅₀₀) and a wet-chemical method. First, 10 mg of the diblock copolymer was dissolved in 1.5 mL of N,N-dimethylformamide (DMF) to form a clear solution, which was then divided into five equal portions. Each portion received 0.8 mL of a Pt (40 mM)/Pd (40 mM)/Ru (80 mM)/Mo (120 mM)/Rh (60 mM) metal salt solution, inducing micellization with hydrophilic PEO shells and hydrophobic PS cores that retained metal ions. The portions were combined and stirred for 2 hours, followed by the addition of 0.3 mL of 6 M hydrochloric acid to adjust the pH. After 30 minutes of further stirring, the mixture was transferred to a preheated oil bath at 95°C. There, 3 mL of formic

acid was introduced as a reducing agent, and the reaction proceeded for 2 hours. Mesoporous HEANP of Ir [m-HEANP(Ir)], Au [m-HEANP(Au)], and Ni [m-HEANP(Ni)] were synthesized by replacing the Mo precursor (MoCl_5) with aqueous solutions of $\text{IrCl}_3 \cdot x\text{H}_2\text{O}$ (40 mM, 0.8 mL), $\text{HAuCl}_4 \cdot 3\text{H}_2\text{O}$ (20 mM, 0.8 mL), and $\text{NiCl}_2 \cdot 6\text{H}_2\text{O}$ (100 mM, 0.8 mL), respectively. All other synthetic parameters, including precursor concentrations, solvent composition, and reaction temperature, were kept constant at the same values used for m-HEANP(Mo). The final product [m-HEANP(Mo)/m-HEANP(Ir)/m-MEANP] was collected by centrifugation (12,000 rpm, 25 min) and washed with acetone, ethanol, and water to remove residual copolymers. Nonporous HEA and MEA nanoparticles [i.e., HEANP(Mo) and MEANP, respectively] were prepared under the same conditions as m-HEANP(Mo) and m-MEANP but in the absence of the block copolymer template, resulting in the formation of non-mesoporous structures.

Similarly, mesoporous HEA film [m-HEAF(Mo)] was synthesized by dissolving 4 mg of the diblock copolymer in 0.6 mL of THF. Subsequently, 0.5 mL of ethanol, 2.32 mL of deionized water, and 0.08 mL of 2 M HCl were added to form a micellar solution at 40°C. A sequential addition of 0.1 mL each of K_2PtCl_4 (40 mM), Na_2PdCl_4 (40 mM), Na_3RhCl_6 (40 mM), $\text{RuCl}_3 \cdot x\text{H}_2\text{O}$ (40 mM), and MoCl_5 (40 mM) was performed to introduce metal precursors into the electrolyte. Electrodeposition was conducted using a conventional three-electrode setup, comprising a Pt wire counter electrode, an Ag/AgCl reference electrode (in 3 M KCl), and an Au-coated Si wafer (3 mm × 15 mm) as the working electrode. The m-HEAF(Mo) was deposited electrochemically at a constant potential of -0.2 V (vs. Ag/AgCl) for 300 s. Following deposition, the working electrode was immersed in THF at room temperature for 24 h to remove the micellar template. For comparison, the m-MEAF was synthesized under identical conditions, excluding MoCl_5 .

Electrocatalytic measurements

Mesoporous high/medium entropy alloy [m-MEANP/m-HEANP(Mo)/m-HEANP(Ir)] nanospheres were ground into a fine powder using a mortar and pestle. In a controlled process, 10 mg of HEAs were dispersed in 5 mL of hexane and sonicated for uniform dispersion. Then, 40 mg of carbon black (Vulcan XC-72) and 30 mL of hexane were added, forming a dark suspension. This mixture underwent 1 hour of sonication at room temperature for improved homogeneity. The resulting powder was collected via high-speed centrifugation (12,000 rpm), washed thrice with ethanol, and dried overnight at 60 °C in a vacuum oven (DP-200, Yamato Scientific Co., Ltd.).

For slurry preparation, 5 mg of the carbon-supported m-MEANP/m-HEANP(Mo)/m-HEANP(Ir) catalysts was dispersed in 950 μL of a 1:2 mixture of deionized water (DI) and isopropanol. A 50 μL addition of 5 wt.% Nafion® solution acted as a binding agent. After 45 minutes of ultrasonication, a homogeneous catalyst ink (5 mg/mL) was obtained and drop-cast (5 μL) onto a glassy carbon rotating disk electrode (RDE, 3 mm diameter). Methanol oxidation reaction (MOR) was conducted in an aqueous 1 M KOH and 1 M methanol solution using a traditional three-electrode setup with graphite rod as a counter electrode, catalysts modified RDE as working, and Hg/HgO (1.0 M NaOH) as the reference electrode. In the case of film samples (m-MEAF/m-HEAF), they were directly used as the working electrodes. The potential measured against Hg/HgO (1 M NaOH) reference electrode was converted to RHE scale using following equation: $E_{(\text{RHE})} = E_{(\text{Hg}/\text{HgO})} + (0.0591 \cdot \text{pH}) + E_{(\text{Hg}/\text{HgO})}^\circ$; where $E_{(\text{Hg}/\text{HgO})}^\circ$ is the standard potential of the Hg/HgO (1.0 M NaOH) electrode (+0.108 V). Before electrochemical measurements, all working electrodes were cleaned electrochemically by cycling them in the potential window of 0.08 to -0.981 V (vs. Hg/HgO) at the scan rate of 100 mV/s in N_2 -saturated 1.0 M KOH electrolyte solution.

The electrochemically active surface area (ECSA) was determined using cyclic voltammogram (CV) profiles recorded in N₂-saturated 1.0 M KOH electrolyte solution in the potential window of 0.03 to -0.871 V (vs. Hg/HgO) at a scan rate of 100 mV/s. To determine the ECSA, the following equation was used: $ECSA = Q_H / q_h$, where Q_H is the charge involved for H-adsorption on various electrocatalysts and q_h is the charge involved in monolayer adsorption of hydrogen on a Pt surface (210 $\mu\text{C}/\text{cm}^2$). The mass activities were determined by normalizing the peak current deduced from MOR CV curves concerning the Pt loading as well as the total metal loading on the working electrodes. The MOR CV curves were recorded in N₂-saturated 1.0 M KOH + 1.0 M CH₃OH electrolyte solution in the potential window of -0.6 to 0.4 V (vs Hg/HgO). The chronoamperometric stability tests were carried out at a constant potential of -0.3 V (vs. Hg/HgO). All electrode potentials were reported in the RHE scale in the manuscript and supporting files.

ASSOCIATED CONTENT

Supporting information (SI): Computational methods, experimental section (materials and characterization), additional figures (Figures S1–S30), and tables (Table S1–S8) (PDF).

The Supporting Information is available free of charge.

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Notes

There are no conflicts to declare.

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TOC Graphic

