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PERSPECTIVE

Opportunities and challenges in protein structure prediction

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Abstract

Deep learning methods, particularly exemplified by AlphaFold2, have revolutionized the field of protein structure prediction—an achievement recognized by the 2024 Nobel Prize in Chemistry awarded to its core developers. Despite this remarkable achievement, the broader protein folding problem is far from solved. Key challenges—each representing opportunities for future breakthroughs—include single-sequence structure prediction, modeling protein dynamics, accurately predicting multimeric complexes, and effectively incorporating experimental constraints. Here we review recent progress in these key frontiers and share our perspective on future directions.

KEYWORDS

cryo-EM, deep learning, protein complexes, protein dynamics, protein structure prediction, single-sequence prediction

1 | INTRODUCTION

Thanks to advancements in artificial intelligence (AI), the past decade has witnessed revolutionary progress in protein structure prediction. Numerous deep learning-based protein structure prediction methods have emerged, significantly boosting performance [1–8]. Among these, AlphaFold2 (AF2) [5] stands out as a landmark achievement, with its core developers receiving the 2024 Nobel Prize in Chemistry. The Critical Assessment of Protein Structure Prediction (CASP) experiments, referred to as the "Olympic Games" of this field, confirmed the superior performance of AF2, which achieved unprecedented, near-experimental accuracy for protein monomers [9]. It now seems that the challenge of single-chain protein structure prediction, a problem pursued for half a century, has been largely solved.

However, the success of AF2 does not mean that the protein folding problem is entirely solved. Several challenges remain where AF2 struggles, which in turn present opportunities for further research. First, AF2's accuracy heavily relies on co-evolutionary signals from multiple sequence alignments (MSAs) [10]. The ability to predict a protein's structure from a single sequence—an approach that more closely aligns with Anfinsen's hypothesis—remains a significant challenge. Second, the prediction of protein dynamics and conformational ensembles remains a largely unexplored frontier. Understanding these dynamic movements is crucial for gaining deeper insights into protein function. Third, although AlphaFold-Multimer (AFM) [11] and AlphaFold3 (AF3) [7] represent major advances in multimeric structure prediction, their accuracy has not yet reached the level of AF2's performance on monomers. This is especially true for difficult targets,

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such as antibody-antigen complexes, where the success rates of deep learning methods are quite low [12]. Finally, complementing de novo prediction, the integration of experimental restraints into deep learning has shown its promise. In this perspective, we will systematically examine recent progress in these key areas and offer our perspective on future directions in the field of protein structure prediction.

2 | SINGLE-SEQUENCE STRUCTURE PREDICTION

Though AF2 achieves near-experimental accuracy for protein monomers, its performance is critically dependent on the quality of the MSA built from a sufficient number of homologous sequences. This reliance introduces two main drawbacks. First, the time-consuming and computationally intensive process of searching for homologous sequences hampers inference efficiency. Second, for “orphan” proteins that lack a deep MSA, AF2 often struggles to produce accurate models. This is particularly true for proteins that evolve rapidly, such as those from viruses, and for antibodies, due to the hypervariability of their complementarity-determining regions. Consequently, on these challenging targets, AF2's advantage over previous methods is significantly diminished [10, 12].

To address this limitation, significant efforts since 2021 have been dedicated to predicting protein structures from a single sequence. These methods typically leverage protein language models (PLMs), such as the Evolutionary Scale Modeling (ESM) series [13, 14], to capture co-evolutionary information directly, bypassing the need for an MSA. A prime example is ESMFold [14], which integrates the ESM2 language model with an AF2-like architecture. Benchmark tests show that ESMFold's performance is competitive with that of AF2, while requiring substantially fewer computational resources and shorter runtimes because it omits the MSA search step. This demonstrates the potential for PLMs to replace the reliance on MSAs. Leveraging its high-throughput advantage, ESMFold was used to predict the structures for over 700 million proteins from metagenomic sequencing, resulting in the creation of a massive structure database (ESM Metagenomic Atlas) [14]. When considering proteins entirely without homologous sequences, trRosettaX-Single has shown relatively superior performance [10, 15]. It outperformed AF2 on “orphan” proteins (though the average Template Modeling score [TM-score] of around 0.5 was still far from satisfactory) and demonstrated high accuracy (average TM-score is about 0.8) on human-designed proteins.

However, blind tests in CASP15 have consistently shown that the overall performance of single-sequence methods, such as ESMFold, is still not on par with MSA-based methods such as AF2 [16]. These methods also struggled to handle orphan targets effectively. The CASP16 assessment also revealed no significant performance difference between groups that employed PLMs and those that did not; in fact, groups not using PLMs performed slightly better [17]. Although an enhanced version, ESM3, was recently proposed for multi-modal protein structure prediction and generation [18], its improvements over the ESM2-based ESMFold were moderate. In fact, when compared at similar parameter levels, its performance was sometimes slightly worse, and it remained generally inferior to the MSA-based AF2.

The limited applicability of current PLM-based methods is understandable, as these models inherently function in a manner analogous to MSA. The quality of embeddings extracted by PLMs largely depends on the diversity of similar sequences within their massive training set, a process that conceptually mirrors searching for homologs in sequence databases. Therefore, it can be argued that current PLM-based approaches are not single-sequence methods in the strictest sense of the term. However, developing a successful paradigm beyond PLMs remains a formidable challenge. At present, the path forward for this field is unclear, and a breakthrough method seems unlikely to emerge in the near future. A possible solution involves generating synthetic homologs via advanced generative models [19–23] that are conditioned on high-throughput experiments such as deep mutational scanning.

3 | DYNAMIC STRUCTURE PREDICTION

Proteins often function through dynamic ensembles of heterogeneous conformations. Although AF2 has revolutionized static structure prediction, capturing this dynamic behavior remains an unresolved and complex challenge [24]. Traditional methods such as molecular dynamics (MD) [25] simulations can be used to explore these motions, but they are computationally expensive and their accuracy can be limited. Consequently, accurately and efficiently predicting the full conformational landscape of a protein—which is crucial for a deep understanding of its function—remains a major challenge in computational biology. To provide a clear overview of this rapidly evolving landscape, the main categories of methods discussed are summarized in Table 1.

In the post-AF2 era, an intuitive first wave of methods sought to leverage the power of static structure predictors to model protein dynamics. The core idea is that the latent space learned by models such as AF2 might implicitly contain information about conformational flexibility. For example, AF2 can be prompted to generate alternative conformations through systematic perturbation of its inputs, such as clustering/

TABLE 1 Representative methods for protein dynamic structure prediction.

Method	Publication year	Characteristics	Reference
AF-Cluster	2024	AF2 + MSA clustering	[26]
Cfold	2024	Retrained AF2 + MSA clustering	[27]
AFsample2	2025	AF2 + random MSA masking	[28]
Frustration-guided AF2	2024	AF2 + energy features	[29]
DCM	2023	Contact map analysis	[30]
trRosettaX2-Dynamics	2025	trX2 + physics-based sampling	[31]
AlphaFold-Metainference	2025	AF2 + MD restraints	[32]
EigenFold	2023	Diffusion model	[33]
ConfDiff	2024	Force-guided diffusion	[34]
DiG	2024	Force-guided diffusion	[35]
AlphaFlow	2024	Flow matching	[36]
P2DFlow	2025	Flow matching	[37]
IDPFold	2025	Diffusion model for IDP	[38]
IDPForge	2025	Diffusion model for IDP	[39]

Abbreviations: AF2, AlphaFold2; DCM, difference contact map; IDP, intrinsically disordered protein; MD, molecular dynamics; MSA, multiple sequence alignment; trX2, trRosettaX2.

masking the MSA, or introducing heterogeneous templates [26–29, 40]. Although these input-perturbation approaches have proven effective for certain proteins, their success often hinges on the availability of a deep and informative MSA. To circumvent this dependency, alternative strategies leverage predicted inter-residue geometries rather than the inputs [30, 31]. A notable example is trRosettaX2 (trX2)-Dynamics [31], which samples from the inter-residue geometry distributions predicted by trX2, offering a physics-based strategy to explore conformational diversity that is less dependent on MSA depth or template existence.

Hybrid methods are also emerging to predict protein dynamics by integrating physical principles with deep learning models. These strategies include using energetic frustration analysis to guide AF2 towards the alternative low-energy conformations [29], and employing Bayesian frameworks such as AlphaFold-Metainference to incorporate experimental data [32]. Such approaches enable the prediction of entire structural ensembles, which is crucial for understanding function and characterizing disordered proteins. However, the systematic, large-scale evaluation and application of these emerging methods have yet to be performed.

Recently, generative modeling has emerged as a powerful paradigm for directly learning conformational distributions [33–39, 41]. Diffusion models [42, 43], in particular, have shown great promise. These methods have evolved from early energy-free approaches [33] to more recent physics-guided frameworks that generate diverse and physically realistic conformations [34, 35]. A related, computationally efficient alternative is flow matching [44], which can learn equilibrium distributions or generate entire transition paths between states [36, 37]. This generative approach is also being successfully tailored to model the challenging structural ensembles of intrinsically disordered proteins [38, 39].

Despite rapid progress, the field of dynamic structure prediction remains in its exploratory phase, facing several foundational challenges. Although generative models show great promise in both generative ability and inference speed, the lack of explicit physical constraints can result in the potential issue of hallucination [45]. Their performance also heavily relies on the conformational dynamics within the training data [27, 45, 46], the scope of which is limited in current public databases such as the Protein Data Bank [47] and the AlphaFold Protein Structure Database [48]. Even when computational methods generate large ensembles, selecting the few biologically meaningful conformations remains a major bottleneck. Although traditional methods such as MD can explore these states, they are often too computationally expensive for large-scale applications.

Therefore, developing hybrid methods that integrate physical principles—such as energy frustration or force fields—into deep learning frameworks is a promising direction for the field. Concurrently, leveraging AI to enhance the efficiency of MD simulations presents another critical avenue for advancement [49], in turn providing crucial dynamic information for training AI methods [45, 46]. A more challenging and essential related problem, protein pathway prediction, has also attracted research interest [50]. In summary, as the field shifts its focus from predicting single static structures to modeling dynamic ensembles, this challenging frontier is where the next breakthrough is anticipated.

4 | MULTIMERIC STRUCTURE PREDICTION

Compared to monomer prediction, predicting the structure of multimeric complexes is a long-standing challenge due to the complicated interaction patterns and weak inter-chain co-evolutionary signals. Table 2 provides a summary of the recent representative deep learning methods for multimeric structure prediction. Before the advent of AF2, mainstream approaches primarily focused on two strategies: elaborate MSA pairing and molecular docking. MSA pairing aims to pair together orthologous sequences between the MSAs of constituent monomers. The goal was to extract the explicit inter-chain co-evolutionary signals in a manner similar to how they are used for protein monomers. However, the application of MSA pairing is limited due to the evolutionary divergence between interacting proteins and the inherent inaccuracies of the heuristic rules used to pair the sequences. Molecular docking computationally assembles predicted monomer structures. This approach, whether rigid or semi-flexible, faces challenges in modeling the significant conformational changes that proteins often undergo upon binding [53].

The advent of AF2 and its successors, AFM [11] and AF3 [7], and RoseTTAFoldAA [8] have significantly advanced the challenging field of multimeric structure prediction. Although it was trained exclusively on monomeric structures, the original AF2 model showed great promise for predicting protein complexes. This was achieved through adaptation techniques such as linker-based sequence concatenation, residue index modification, and/or integration with docking protocols [54–56]. Interestingly, AF2 can often yield accurate predictions without explicit MSA pairing [54]. On the other hand, the traditional MSA pairing, now enhanced by deep learning or larger databases, is showing renewed potential to further improve the accuracy of AF2's predictions [51, 52, 57, 58]. It remains unclear how important MSA pairing is to AlphaFold-based complex structure prediction.

AFM incorporated specific modifications upon AF2 for complex structure prediction, further improving interface accuracy while maintaining intra-chain folding quality. The impact was dramatic: the introduction of AFM improved the success rate of interface prediction from 31% in CASP14 to about 90% in CASP15 [59, 60]. More recently, employing a diffusion-based architecture, AF3 has shown further moderate improvements in protein complex prediction [7]. Leveraging the unique strengths of AFM and AF3, our groups have achieved leading performance in multimeric structure prediction in both CASP15 [61] and CASP16 [62].

Despite recent progress, the prediction of multimeric protein structures is far from solved. Several key challenges remain. First, the accurate modeling of the large, heteromeric complexes continues to be difficult, especially when the stoichiometry is unknown, as highlighted in the CASP16 report [63]. Second, although large-scale sampling can generate high-quality models, a reliable scoring function to select the best candidate from the resulting pool is still a bottleneck in the field. Encouragingly, this challenge is being addressed, thanks to the proposal of new quality assessment methods for protein complexes [64–66]. Third, although the AlphaFold-based methods do not require inter-chain co-evolutionary priors, they still struggle when intra-chain signals are weak or absent. This is a common scenario for antibody-antigen complexes [12], which are critically important for fields such as drug discovery and therapeutic development. Fortunately, the Kozakov group in CASP16 demonstrated promising results on these challenging antibody-antigen targets using traditional docking methods with extensive sampling [63]. This success suggests that the future of the field may lie in a powerful collaboration between deep learning and physicochemical restraints.

5 | EXPERIMENTAL DATA-ASSISTED STRUCTURE PREDICTION

Although AlphaFold-series methods have illustrated their great power for general-purpose protein structure prediction, they still struggle with certain protein systems, such as large protein assemblies. In such cases, support from experimental data becomes crucial. Fortunately, cryo-electron microscopy (cryo-EM) has emerged as a powerful tool for experimentally determining large protein complexes. In recent years, deep learning techniques have increasingly been developed to integrate and leverage cryo-EM data. We categorize the deep learning methods for cryo-EM modeling into two main types: one combines protein structure prediction with structure fitting, whereas the other is based on de novo model building. The former approach emerged due to the low resolution of early cryo-EM maps, which made it difficult to identify key structural features, necessitating a mixed method relying on structure prediction, fitting, and assembly. The latter approach has become feasible as advancements in experimental instruments, data processing software, and experimental protocols have continuously improved the resolution of density maps, allowing for de

TABLE 2 Representative methods for protein multimeric structure prediction.

Method	Publication year	Characteristics	Reference
AFM	2021	Modified AF2 architecture retrained on complexes	[11]
AlphaFold3	2024	Diffusion model for generalized biomolecule prediction	[7]
RoseTTAFoldAA	2024	RoseTTAFold extension for generalized biomolecule modeling	[8]
DMfold	2024	Enhanced MSA construction by DeepMSA2	[51]
DeepSCFold	2025	Enhanced MSA pairing via deep learning	[52]

Abbreviations: AF2, AlphaFold2; AFM, AlphaFold-Multimer; MSA, multiple sequence alignment.

TABLE 3 Representative deep learning methods for cryo-EM modeling of protein structures from cryo-EM density maps.

Method	Publication year	Characteristics	Reference
ModelAngelo	2024	De novo model building	[67]
Cryo2Struct	2024	De novo model building	[68]
CryoAtom	2025	De novo model building	[69]
EModelX	2024	Fitting the density map with the predicted structure	[70]
EMProt	2025	Fitting the density map with the predicted structure	[71]
DiffModeler	2024	Fitting the density map with the predicted structure	[72]

Abbreviation: cryo-EM, cryo-electron microscopy.

novo model building. A summary of the methods discussed here can be found in Table 3.

A typical deep learning-based method for cryo-EM modeling adopts a two-stage approach. In the first stage, variants of 3D convolutional neural networks are used to extract information about the protein backbone structure from the density map. The differences among them often lie in the strategies for building atomic models in the second stage. For example, EMBuild [73], EModelX [70], EMProt [71] and DiffModeler [72] fit the structures predicted by AF2 [5] with the backbone structures extracted from the density map. Cryo2Struct [68] relies on traditional chain tracing and sequence alignment algorithms. ModelAngelo [67] employs graph neural networks to construct atomic models. CryoAtom [69] reduces the resolution requirements of the density map using local attention and 3D rotary position embedding. In terms of results, de novo modeling methods can achieve accuracy comparable to that of human experts on high-resolution density maps, whereas their performance on low-resolution density maps may be inferior to that of the "fitting" approaches. This indicates that experimental data and structure prediction are complementary. The high-resolution regions of the density map can provide strong constraints for structure prediction, whereas the low-resolution regions require external information to supplement, such as structure predictions derived from single sequences or MSAs.

In addition to integrating cryo-EM data, there has been recent use of cross-linking mass spectrometry (MS) to provide distance constraints useful for protein structure prediction. MS is a technique that combines chemical crosslinking with MS analysis [74, 75], which can provide inter-residue constraints and can be used to study protein structure and protein-protein interactions. A representative method is AlphaLink [76], which successfully incorporates these distance constraints into the pair representation of AF2, enhancing the accuracy of protein structure prediction. AlphaLink has also been extended to AFM for protein complex prediction, where it shows particular promise for challenging antibody-antigen complexes—a known area of difficulty for standard AlphaFold-based methods [77].

Experimental data from cryo-EM and cross-linking MS can provide valuable constraints for structure predictions. This creates a multimodal landscape where 1D sequences, 2D MS-derived distance restraints, and 3D density maps serve as complementary sources of information. For orphan proteins such as antibody-antigen complexes that lack deep MSAs, incorporating MS and high-resolution density maps can significantly improve prediction accuracy. Conversely, for low-resolution regions within a density map, information from MSAs and MS can be used to achieve higher precision. It is expected that multimodal models capable of integrating these diverse data types will be a major trend in future development. The key to advancing this frontier will be discovering the most effective ways to fuse these different information sources.

6 | CONCLUSIONS

Although deep learning has revolutionized protein structure prediction, several important challenges remain, and progress across these frontiers has been uneven. Single-sequence structure prediction appears to have encountered a bottleneck. Current methods based on PLMs have shown their limits, whereas a truly novel, alternative paradigm remains elusive. In contrast, the field of dynamic structure prediction is rapidly advancing, powered by progress in generative models and AI-accelerated MD. Despite certain challenges, the study of protein dynamics represents a promising frontier poised to deliver the next major breakthrough in protein science. Multimeric structure prediction, though greatly enhanced by AFM and AF3, also remains an unsolved challenge. However, the success of traditional docking approaches for antibody-antigen prediction in CASP16 highlights a promising path forward: integrating the predictive power of AI with physics-based methods. Finally, the incorporation of experimental restraints from techniques such as cryo-EM and MS shows great potential for further enhancing prediction accuracy.

In conclusion, the field's key challenges—single-sequence, dynamic, and multimeric prediction—all share a common bottleneck: they operate in domains where the deep evolutionary information that powered AlphaFold is sparse, absent, or insufficient. We argue that the path forward lies in a paradigm shift: from prediction based on evolutionary data to modeling constrained by physics and experimental data. The future, therefore, will be defined by integration. First, the predictive power of AI must be integrated with the rigor of physical principles. This trend is already evident in the rise of AI-accelerated MD and the success of traditional, physics-based docking for challenging multimeric targets where AI fails. Second, it is promising to develop next-generation models capable of integrating multi-modal data. The critical biological problems, such as modeling antibody-antigen complexes or interpreting low-resolution cryo-EM maps, demand a unified framework that can simultaneously leverage 1D sequences, 2D distance restraints (MS), and 3D density maps (cryo-EM).

Therefore, the next breakthrough may not be merely a better structure predictor, but a holistic modeling framework. Discovering the most effective ways to fuse these complementary information sources is the key to finally moving beyond static snapshots and truly modeling the dynamic, functional landscape of biology.

AUTHOR CONTRIBUTIONS

Wenkai Wang: Formal analysis; investigation; writing—original draft; writing—review and editing. **Baoquan Su**: Formal analysis; investigation; writing—original draft. **Chenxiao Xiang**: Formal analysis; investigation; writing—original draft. **Jianyi Yang**: Conceptualization; formal analysis; project administration; supervision; writing—review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

ETHICS STATEMENT

This review article is based on a comprehensive analysis of existing literature and does not involve human or animal subjects, experimental research, or personal data collection.

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