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# A Helper for Patenting the “Unpredictable”: Artificial Intelligence

Shuang Liu\*

## INTRODUCTION

A patent is a limited-term exclusive right over a claimed invention.<sup>1</sup> In return for this exclusive right, society obtains not just a new piece of “art,”<sup>2</sup> but also “the technological know-how behind the inventor’s patent.”<sup>3</sup> Therefore, it is an “indispensable condition in all patents, that the patentee<sup>4</sup> shall ascertain the nature of his invention, and in what manner it is to be

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1. “A patent is not the grant of a right to make or use or sell. It does not, directly or indirectly, imply any such right. It grants only the right to exclude others.” *Herman v. Youngstown Car Mfg. Co.*, 191 F. 579, 584 (6th Cir. 1911); *see also* 35 U.S.C. § 271. In the United States, the patent term for a utility patent is twenty years, 35 U.S.C. § 154(a)(2), for a design patent fifteen years, 35 U.S.C. § 173, and for a plant patent twenty years, 35 U.S.C. § 161 (“The provisions of this title relating to patents for inventions shall apply to patents for plants, except as otherwise provided.”).

2. In the context of patent law, the term “art” is often used as a synonym for “technology.” This Note uses “art” in the same way.

3. ROBERT P. MERGES & JOHN F. DUFFY, *PATENT LAW AND POLICY* 247 (7th ed. 2017).

4. A patentee, also an assignee, is a person or entity that holds a patent right. *See* 35 U.S.C. § 100(d) (1952). Relatedly, an applicant is a person or entity that applies for a patent. *See* 37 C.F.R. § 1.42(a). An inventor is a person who invents what is sought to be patented. *See* 35 U.S.C. § 100(f) (1952). Although the patentee/assignee, applicant, and inventor can be different for a given patent, this Note uses these terms equivalently to avoid unnecessary complexity.

performed.”<sup>5</sup> This “indispensable condition” is embedded in the enablement requirement and the written description requirement under 35 U.S.C. § 112(a):

The specification<sup>6</sup> shall contain a *written description* of the invention, and of the manner and process of making and using it, in such full, clear, concise, and exact terms as to *enable* any person skilled in the art to which it pertains, or with which it is most nearly connected, to make and use the same . . . .<sup>7</sup>

For the purpose of patent law, “the invention” is the claim.<sup>8</sup> Claims define the “metes and bounds” of the patentee’s intellectual property.<sup>9</sup> It is against the *full scope of claims* that the patentee is required to provide a sufficient disclosure satisfying the enablement and written description requirements.<sup>10</sup> That is, for a claim to be valid, among other requirements, the patent document must contain enough disclosure such that “a person having ordinary skill in the art” (PHOSITA)<sup>11</sup> is able to recognize what the patentee claims as

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5. THOMAS G. FESSENDEN, AN ESSAY ON THE LAW OF PATENTS FOR NEW INVENTIONS 48–49 (1st ed. 1810); *see also* Pfaff v. Wells Elecs., Inc., 525 U.S. 55, 63 (1998) (“[T]he patent system represents a carefully crafted bargain that encourages both the creation and the public disclosure of new and useful advances in technology, in return for an exclusive monopoly for a limited period of time.”).

6. Under 35 U.S.C. § 111(a)(2) (1952), a patent application shall include a specification, a drawing, and an inventor’s (or inventors’) oath or declaration. The specification usually includes sections of abstract, background, summary of invention, detailed description of invention, and claims. *See* MPEP § 608.01 (9th ed. Rev. 10.2019, June 2020). An applicant commonly describes the invention in the summary of invention and detailed description of invention sections with drawings, if any.

7. 35 U.S.C. § 112(a) (1952) (emphasis added).

8. *See* Jones v. Hardy, 727 F.2d 1524, 1528 (Fed. Cir. 1984) (“[E]ach claim must be considered as defining a separate invention.” (citation omitted)).

9. *In re Vamco Mach. & Tool, Inc.*, 752 F.2d 1564, 1577 n.5 (Fed. Cir. 1985) (“The function of claims is (a) to point out what the invention *is* in such a way as to distinguish it from what was previously known, i.e., from the prior art; and (b) to define the *scope of protection* afforded by the patent. In both of those aspects, claims are not technical descriptions of the disclosed inventions but are legal documents like the descriptions of lands by metes and bounds in a deed which *define* the area conveyed but *do not describe the land*.” (emphasis added)).

10. *See In re Wright*, 999 F.2d 1557, 1561 (Fed. Cir. 1993) (“Although not explicitly stated in [35 U.S.C. §] 112, to be enabling, the specification of a patent must teach those skilled in the art how to make and use the *full scope* of the claimed invention without ‘undue experimentation.’” (emphasis added) (citations omitted)).

11. A PHOSITA is a “hypothetical person who is presumed to be aware of all the pertinent prior art.” *Custom Accessories, Inc. v. Jeffrey-Allan Indus.*,

the invention, to practice<sup>12</sup> the full scope of the claimed invention, and to see that the patentee has actually made the invention, or is in “possession” of it.<sup>13</sup>

However, for technologies of different nature, the required amounts of disclosure for enablement purposes are in sharp distinction. As the *Fisher* court famously stated:

In cases involving predictable factors, such as mechanical or electrical elements, a single embodiment<sup>14</sup> provides broad enablement in the sense that, once imagined, other embodiments can be made without difficulty and their performance characteristics predicted by resort to known scientific laws. In cases involving unpredictable factors, such as most chemical reactions and physiological activity, the scope of enablement obviously varies inversely with the degree of unpredictability of the factors involved.<sup>15</sup>

By the same token, the required amount of disclosure for showing possession of an invention varies by arts.<sup>16</sup> For example, consider a scenario where a patentee invents a machine comprising a connection component and describes the connection component by a nail. The patentee is then obviated from describing a machine comprising a screw as the connection component but can still show that he or she has invented<sup>17</sup> such

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Inc., 807 F.2d 955, 962 (Fed. Cir. 1986) (citation omitted). See *infra* Section I.A.1.b for details.

12. In the context of patent law, “practicing a claim” generally means making and using a claim. This Note uses the phrase in the same way.

13. *In re Kaslow*, 707 F.2d 1366, 1375 (Fed. Cir. 1983) (“The test for determining compliance with the written description requirement is whether the disclosure of the application as originally filed reasonably conveys to the artisan that the inventor had *possession* at that time of the later claimed subject matter, rather than the presence or absence of literal support in the specification for the claim language.” (emphasis added) (citations omitted)).

14. In the context of patent law, the term “embodiment” usually refers a concrete example of an invention. See Tom Brody, *Preferred Embodiments in Patents*, 9 J. MARSHALL REV. INTELL. PROP. L. 398, 398 (2009) (“It is a tradition in patent drafting to refer to . . . examples as . . . ‘embodiment[s].’”).

15. *In re Fisher*, 427 F.2d 833, 839 (C.C.P.A. 1970).

16. See *Ariad Pharms., Inc. v. Eli Lilly & Co.*, 598 F.3d 1336, 1351 (Fed. Cir. 2010) (“Specifically, the level of detail required to satisfy the written description requirement varies depending on the nature and scope of the claims and on the complexity and predictability of the relevant technology.” (citation omitted)).

17. Under patent law, an invention is made when there is a conception and a reduction to practice. *Dunn v. Ragin*, 50 U.S.P.Q. 472, 474 (B.P.A.I. 1941). “The conception of the invention consists in the complete performance of the mental part of the inventive art . . . . It is . . . the formation in the mind of the inventor of a definite and permanent idea of the complete and operative invention . . . .” *Townsend v. Smith*, 36 F.2d 292, 295 (C.C.P.A. 1929). Reduction

a machine. In contrast, consider another hypothetical in which a patentee invents a new drug for a disease X, and the drug comprises a main structure M and an element A attached to the main structure. The patentee cannot declare to the public that he or she has also invented a drug comprising the main structure M and an element B without disclosing it in the specification. After all, changing one element of a drug might render it no longer effective for its purpose and even cause unintended effects.<sup>18</sup> Accordingly, the patentee in the first example is able to support a claim of “a machine comprising a connection component” by describing the machine with a nail as the connection component, but the patentee in the second example is unable to support a claim of “a drug comprising a main structure M and an element” by providing the experiment results of only the compound with element A attached to the main structure M.<sup>19</sup> It is then obvious that the enablement and written description requirements are posing more difficulties for “genus claims”<sup>20</sup> in unpredictable arts than predictable arts to

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to practice may be an actual reduction or a constructive reduction to practice. *Dunn*, 50 U.S.P.Q. at 472. Establishing “an actual reduction to practice [requires] (1) the [applicant to] construct[] an embodiment or perform[] a process that [meets] every element of the interference count, and (2) the embodiment or process [to] operate[] for its intended purpose.” *Eaton v. Evans*, 204 F.3d 1094, 1097 (Fed. Cir. 2000). In contrast, a constructive reduction to practice can be done by filing a patent application which satisfies the enablement and written description requirements. *Hyatt v. Boone*, 146 F.3d 1348, 1352 (Fed. Cir. 1998). Accordingly, in this hypothetical scenario, the patentee has “invented” the machine comprising a screw by a conception and a constructive reduction to practice.

18. See, e.g., *Idenix Pharms. LLC v. Gilead Scis. Inc.*, 941 F.3d 1149, 1155 (Fed. Cir. 2019) (“[I]n the nucleoside area[, a specific type of chemicals,] . . . the smallest change can have a dramatic effect not only on the activity of that compound but on the toxicity of the compound. So nothing is predictable.” (quotation mark omitted) (citation omitted)).

19. See *infra* notes 145–47 and accompanying text for real cases presenting this issue.

20. A genus claim, also called a “generic claim,” is a claim that covers more than one species, where the “generic claim should require no material element additional to those required by the species claims, and each of the species claims must require all the limitations of the generic claim.” MPEP § 806.04(d) (9th ed. Rev. 10.2019, June 2020). Specifically, in the first one of preceding examples, the genus claim is “a machine comprising a connection component,” and a species claim is “a machine comprising a connection component, wherein the connection component is a nail”; similarly, in the second example, the genus claim is “a drug for a disease X, comprising a main structure M and an element,” and a species claim is “a drug for a disease X, comprising a main structure M and an element, wherein the element is A.”

stand valid before either the Patent and Trademark Office (PTO) or courts.<sup>21</sup>

A potential response to this difficult situation is to claim narrowly: if the claim covers only one species that is fully described by the embodiments, it will undoubtedly meet the enablement and written description requirements. But a patent is only valuable in the context of business.<sup>22</sup> Narrow claims afford only a weak protection to a patentee because a competitor can easily find variations of the patentee's inventions without infringing the narrowly-claimed patents.<sup>23</sup> This problematic reality compels patent applicants to claim broadly, even as the PTO and courts are making such practice harder and harder.<sup>24</sup>

Another solution to this dilemma is to invent the genus—that is, to not only conceive how to obtain the species of the genus, but also know what the species are.<sup>25</sup> This solution might sound trivial because, if an applicant can afford the time and money to experiment with every species in the entire genus, the problem posed above should have not existed to begin with. But this solution is actually practical because it is possible to invent

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21. See Sean B. Seymore, *Heightened Enablement in the Unpredictable Arts*, 56 UCLA L. REV. 127, 136–37 (2008).

22. See Michael K. Henry, *Claim Strategies for Patent Applications: Can Your Patent Claims Ever Be Too Narrow?*, HENRY (Dec. 7, 2017), <https://henry.law/blog/can-your-patent-claims-ever-be-too-narrow/> (“Patents are, first and foremost, business tools. They can help protect your invention’s commercial value or offer your business an advantage over its competitors.”); see also Joan Farre-Mensa et al., *What Is a Patent Worth? Evidence from the U.S. Patent “Lottery”*, 75 J. FIN. 639, 639 (2020) (“In theory, patents can benefit their holders by deterring copycats and by serving as defensive shields in litigation suits, as bargaining chips in licensing negotiations, and as signaling devices to attract investors and customers.”).

23. See *Quality Patents: Claiming What Counts*, WIPO MAG., Jan./Feb. 2006, at 17, 18 (“[B]road claims are attractive to the business applicant because they cover a greater range of products or situations . . . . Conversely, [narrow claims] will prove less useful as a business tool since they allow competitors to gain easy access to the same market by producing products with only minor modifications to the patented product or service.”); see also Henry, *supra* note 22.

24. See generally Dmitry Karshtedt et al., *The Death of the Genus Claim*, 35 HARV. J.L. & TECH. 1 (2021).

25. If an applicant is able to describe (1) what the species are, and (2) how to make and use them, the applicant will be able to file an application that satisfies the enablement and written description requirement, and thereby constructively reduce the invention. See *supra* note 17. In this sense, the applicant invents the genus by a conception and a constructive reduction to practice. See *id.*

the whole genus without experimenting with all species covered by it. The secret for doing so is Artificial Intelligence (AI).

AI is generally understood as a machine simulating human thinking and actions in response to a situation.<sup>26</sup> Many modern inventions are made possible by AI, such as language recognition (e.g., Siri<sup>27</sup> and Alexa<sup>28</sup>), smart recommendations (e.g., TikTok,<sup>29</sup> YouTube,<sup>30</sup> and Amazon<sup>31</sup>), and self-driving cars (e.g., Tesla<sup>32</sup>). Scientists are also developing AI for research purposes. For example, Naik et al. developed an AI for predicting whether a given drug has some effects on a given protein.<sup>33</sup> Once fed with

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26. There is no universal definition of AI. The concept of AI stemmed from the seminal work, Alan M. Turing, *Computing Machinery and Intelligence*, 59 MIND 433 (1950), in which Dr. Turing proposed a test for telling whether a machine possessed intelligence (now famously known as the “Turing Test”). Upon the pass of the Turing test, a machine can be said to possess intelligence. *Id.* at 433–34. Later, Dr. McCarthy provided a definition of AI: “It is the science and engineering of making intelligent machines, especially intelligent computer programs. It is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable.” JOHN MCCARTHY, WHAT IS ARTIFICIAL INTELLIGENCE? 2 (2004). In a classical AI textbook, Dr. Russell and Dr. Norvig summarized various definitions of AI, all of which are related to a machine thinking and/or acting humanly and/or rationally. STUART J. RUSSELL & PETER NORVIG, ARTIFICIAL INTELLIGENCE: A MODERN APPROACH 2 (3d ed. 2010).

27. See, e.g., William Goddard, *Is Siri AI?*, ITCRONICLES (Nov. 23, 2020), <https://itchronicles.com/artificial-intelligence/is-siri-ai/> (“Siri is a system that uses artificial intelligence . . .”).

28. See, e.g., *What Is Conversational AI?*, ALEXA, <https://developer.amazon.com/en-US/alexa/alexa-skills-kit/conversational-ai> (last visited Jan. 12, 2022) (“With conversational AI, voice-enabled devices like Amazon Echo are enabling the sort of magical interactions we’ve dreamed of for decades.”).

29. See, e.g., Catherine Wang, *Why TikTok Made Its User So Obsessive? The AI Algorithm That Got You Hooked*, TOWARDS DATA SCI. (June 7, 2020), <https://towardsdatascience.com/why-tiktok-made-its-user-so-obsessive-the-ai-algorithm-that-got-you-hooked-7895bb1ab423>.

30. See, e.g., Aratrika Dutta, *How Does Youtube Algorithm Work? The Use of AI for Video Recommendations*, ANALYTICS INSIGHT (Oct. 21, 2021), <https://www.analyticsinsight.net/how-does-youtube-algorithm-work-the-use-of-ai-for-video-recommendations/>.

31. See, e.g., *3 Ways Amazon Uses AI to Make Product Recommendations*, LINEATE (Dec. 16, 2019), <https://www.lineate.com/technology-insights/3-ways-amazon-uses-ai-to-make-product-recommendations>.

32. See, e.g., *Artificial Intelligence & Autopilot*, TESLA, <https://www.tesla.com/AI> (last visited Jan. 12, 2022) (“We believe that an approach based on advanced AI for vision and planning, supported by efficient use of inference hardware, is the only way to achieve a general solution for full self-driving and beyond.”).

33. Armaghan W. Naik et al., *Active Machine Learning-Driven Experimentation to Determine Compound Effects on Protein Patterns*, ELIFE,

initial proteins and drugs, the AI operates to determine what combinations of proteins and drugs it needs to experiment with to allow or improve its predictions.<sup>34</sup> It then performs experiments with its liquid-handling robotics and repeats the determination-experimentation cycle until the end condition set by the developers is triggered.<sup>35</sup> In an attempt to predict the effects forty-eight different drugs would have on forty-eight different proteins, the AI experimented with 29% of all possible combinations<sup>36</sup> and reached a 92% prediction accuracy.<sup>37</sup> Similarly, AI with impressive prediction capabilities have emerged for many other applications, including predicting myriad structures and properties of existing or prospective materials,<sup>38</sup> potency and other properties of drug candidates,<sup>39</sup> *de novo* materials<sup>40</sup> and drugs<sup>41</sup> for given purposes, new uses of FDA-approved drugs,<sup>42</sup> and promising synthesis routes for drugs.<sup>43</sup>

These inspiring results highlight the plausibility for patent practitioners to file claims within the capability of a well-developed AI—claims that are broader than just one or two experimentally-confirmed species but narrow enough to be enabled and described by the AI predictions. Accordingly, this Note discusses how applicants can utilize AI to file genus claims in the traditionally unpredictable arts and experiment with only a few species, while minimizing risks of enablement and written description challenges.

The interaction between AI and patent law has been discussed by a few scholars.<sup>44</sup> Most relevantly, Ebrahim

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Feb. 3, 2016, at 1, 2 (“[O]ur goal is to identify whether a given drug perturbs the pattern of a given protein, and symmetrically, which drugs perturb which proteins in a similar manner.”).

34. *Id.* at 3–4.

35. *Id.*

36. In this work, Naik et al. duplicated each drug and each protein, but the duplication was not revealed to the AI. *Id.* Therefore, there were 96 x 96 = 9,216 combinations in total. *Id.* at 3.

37. *Id.* at 7 fig. 2.

38. See *infra* note 202.

39. See *infra* Section II.B.1.

40. See *infra* note 203.

41. See *infra* Section II.B.2.a.

42. See *infra* Section II.B.2.b.

43. See *infra* Section II.B.3.

44. See, e.g., Russ Pearlman, *Recognizing Artificial Intelligence (AI) as Authors and Inventors Under U.S. Intellectual Property Law*, 24 RICH. J.L. &

discussed the challenges posed by computation-based simulation<sup>45</sup> and machine-learning-based prediction<sup>46</sup> (collectively, “computational experiments”) in the traditionally unpredictable arts.<sup>47</sup> Specifically, Ebrahim argued that computational experiments “can enable an inventor to make a patent application appear as if experimental data has been achieved when, in fact, there have been only computational simulations of hypothetical experiments,”<sup>48</sup> and in response, the PTO and courts should strengthen the utility requirement and make experiment-based working examples a necessary part of disclosure for computational-experiment-based patent applications.<sup>49</sup> In contrast, this Note focuses on how patent practitioners can properly utilize AI predictions to satisfy the enablement and written description requirements under current patent law. More particularly, this Note discusses various AI-assisted patent practices that take into account the concrete facts of AI predictions, including what specific areas AI can make satisfactory prediction and how accurate those predictions are.<sup>50</sup> This Note also briefly explains how to provide a disclosure that meets the enablement and written description requirements, and how much experimentation is needed for that

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TECH. 2 (2018); Rachel L. Schwein, *Patentability and Inventorship of AI-Generated Inventions*, 60 WASHBURN L.J. 561 (2021); Lucas R. Yordy, *The Library of Babel for Prior Art: Using Artificial Intelligence to Mass Produce Prior Art in Patent Law*, 74 VAND. L. REV. 521 (2021); Daria Kim, ‘AI-Generated Inventions’: Time to Get the Record Straight?, 69 GRUR INT’L 443 (2020); Tabrez Y. Ebrahim, *Computational Experimentation*, 21 VAND. J. ENT. & TECH. L. 591 (2019).

45. Computation-based simulation is an approach in which molecular properties can be computed according to established scientific models. *See infra* note 152.

46. Machine learning is a major portion of currently available AI. *See infra* notes 153–154 and accompanying text.

47. Ebrahim, *supra* note 44, at 593.

48. *Id.* at 607.

49. *See id.* at 613–49. This Note does not endorse this argument by quoting and paraphrasing it. An applicant cannot “make a patent application appear as if experimental data has been achieved” when no real experimentation has been performed without committing “inequitable conduct,” which would render a patent unenforceable. *See, e.g., J.P. Stevens & Co. v. Lex Tex Ltd., Inc.*, 747 F.2d 1553, 1559 (Fed. Cir. 1984) (“[Inequitable conduct] includes failure to disclose material information, or submission of false material information, with an intent to mislead.”). Alternatively, if the applicant is honest and reveals the examples are prophetic, then such examples are nothing special and can be readily handled by current law. *See infra* text accompanying notes 96–97.

50. *See infra* Sections III.A.1–2.

purpose.<sup>51</sup> In addition, this Note discusses the potential negative effects of AI predictions on obviousness challenges and provides suggestions for overcoming them in practice.<sup>52</sup>

This Note proceeds in three parts. Part I surveys the current case law on the enablement and written description requirements in detail. Part II briefly introduces (1) the work principles of AI, (2) the applications of AI in the traditional unpredictable arts, especially in drug discovery, and (3) the accessibility and limitations of AI. Part III describes several AI-assisted patent practices and specifically recommends one of them. It goes on to present the incapability of current patent law to deal with some problems posed by AI-assisted patent practice, followed by some proposed solutions. Finally, it defends the AI-assisted patent practice from a policy perspective and proposes a solution to a potential equity concern raised by the inaccessibility of some AI resources.

### I. CASE LAW ON THE ENABLEMENT AND WRITTEN DESCRIPTION REQUIREMENTS

To perceive how AI predictions can help satisfy the enablement and written description requirements, an in-depth understanding of current law on these two issues will be very helpful. Accordingly, this Section discusses the law related to these two requirements in detail.

Procedurally, the enablement and written description requirements, among other requirements, play a role when the PTO examines a patent application and when a patent is challenged before the Patent Trial and Appeal Board (PTAB) or courts. Therefore, an application needs to satisfy the enablement and written description requirements to become a patent, and a patent must satisfy these requirements to maintain its validity when challenged.<sup>53</sup> The case law discussed in this Section includes those before the PTAB,<sup>54</sup> the Federal Circuit Court<sup>55</sup>

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51. *See id.*

52. *See infra* Section III.A.3.

53. 35 U.S.C. § 112(a).

54. The Board of Patent Appeals and Interferences (BPAI) is the predecessor of the PTAB. This Note discusses the cases before the BPAI equivalently as those before the PTAB.

55. The United States Court of Customs and Patent Appeals (CCPA) is the predecessor of the Federal Circuit Court with respect to the jurisdiction over

and the U.S. Supreme Court, all of which bind the PTO and are thus also applicable to the patent examination process.<sup>56</sup> Rules and guidance from the PTO are also cited; these rules and guidance bind the examiners only,<sup>57</sup> but courts do refer to them when found to be persuasive.<sup>58</sup>

#### A. THE ENABLEMENT REQUIREMENT

To satisfy the enablement requirement under 35 U.S.C. § 112, “the specification must teach those skilled in the art how to make and use the full scope of the claimed invention without ‘undue experimentation.’”<sup>59</sup> Hence, enablement issues arise when the scope of the claim is broader than the guidance provided by the specification and a PHOSITA is unable to fill the “gap” without “undue experimentation.”<sup>60</sup> How much experimentation counts as “undue” is “a matter of degree”;<sup>61</sup> it is determined by the factors established by the Federal Circuit Court in *In re Wands* (hereinafter the *Wands* factors).<sup>62</sup>

##### 1. The *Wands* Factors

The *Wands* factors include:

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patent-related cases. This Note discusses the cases before the CCPA equivalently as those before the Federal Circuit Court.

56. See 35 U.S.C. § 144 (“The United States Court of Appeals for the Federal Circuit shall review the decision from which an appeal is taken on the record before the Patent and Trademark Office.”).

57. It is controversial whether the PTAB is bound by the PTO’s guidance. See Kevin E. Noonan, *Who’s in Charge Here? Or Is the PTAB Bound by USPTO Guidances?*, PATENT DOCS (Feb. 19, 2018), <https://www.patentdocs.org/2018/02/whos-in-charge-here-or-is-the-ptab-bound-by-uspto-guidances.html>.

58. See *In re Fisher*, 421 F.3d 1365, 1372 (Fed. Cir. 2005) (concluding that even though the PTO’s guidance “govern[s] [the USPTO’s] internal practice[s]” and the USPTO “incorporated these guidelines into the [MPEP],” “[t]he MPEP and Guidelines are not binding on this court” but they “may be given judicial notice to the extent they do not conflict with the statute”); see also *In re Biogen ‘755 Patent Litigation*, 335 F. Supp. 3d 688, 734 (D.N.J. 2018) (“While not binding on this Court, the PTO’s guidance is nevertheless persuasive.”).

59. *In re Wright*, 999 F.2d 1557, 1561 (Fed. Cir. 1993).

60. See *AK Steel Corp. v. Sollac*, 344 F.3d 1234, 1244 (Fed. Cir. 2003) (“That is not to say that the specification itself must necessarily describe how to make and use every possible variant of the claimed invention, for the artisan’s knowledge of the prior art and routine experimentation can often fill gaps, interpolate between embodiments, and perhaps even extrapolate beyond the disclosed embodiments, depending upon the predictability of the art.”).

61. *PPG Indus., Inc. v. Guardian Indus. Corp.*, 75 F.3d 1558, 1564 (Fed. Cir. 1996).

62. *In re Wands*, 858 F.2d 731 (Fed. Cir. 1988).

(1) [T]he quantity of experimentation necessary, (2) the amount of direction or guidance presented, (3) the presence or absence of working examples, (4) the nature of the invention, (5) the state of the prior art, (6) the relative skill of those in the art, (7) the predictability or unpredictability of the art, and (8) the breadth of the claims.<sup>63</sup>

These will be elaborated upon with relevant factors grouped together.

#### a. Scope of Claims

Although listed last in the *Wands* factors, determination of the scope of claims should actually be the first step of the enablement analysis.<sup>64</sup> A claim is given a scope of “its broadest reasonable construction in light of the specification of the application or patent in which it appears” (hereinafter the BRI standard)<sup>65</sup> during patent examination,<sup>66</sup> and a scope of the claim “would have to a [PHOSITA] at the time of the invention” (hereinafter the *Phillips* standard)<sup>67</sup> in post-issuance procedures.<sup>68</sup> While the BRI standard may possibly render a

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63. *Id.* at 737 (citation omitted).

64. See MPEP § 2164.08 (9th ed. Rev. 10.2019, June 2020) (“All questions of enablement are evaluated against the claimed subject matter . . . . Accordingly, the first analytical step requires that the examiner determine exactly what subject matter is encompassed by the claims.”); see also *supra* note 10 and accompanying text.

65. “Under a broadest reasonable interpretation (BRI), words of the claim must be given their plain meaning, unless such meaning is inconsistent with the specification. The plain meaning of a term means the ordinary and customary meaning given to the term by those of ordinary skill in the art at the time of the invention. The ordinary and customary meaning of a term may be evidenced by a variety of sources, including the words of the claims themselves, the specification, drawings, and prior art.” MPEP § 2111.01.I (9th ed. Rev. 10.2019, June 2020).

66. *Koninklijke Philips Elecs. N.V. v. Cardiac Sci. Operating Co.*, 590 F.3d 1326 (Fed. Cir. 2010).

67. *Phillips v. AWH Corp.*, 415 F.3d 1303, 1313 (Fed. Cir. 2005) (en banc).

68. See *Changes to the Claim Construction Standard for Interpreting Claims in Trial Proceedings Before the Patent Trial and Appeal Board*, 83 Fed. Reg. 21,221-1, 21,223-2 (Oct. 11, 2018) (“This proposed change would replace the BRI standard for construing unexpired patent claims and proposed claims in IPR, PGR, and CBM proceedings with an approach that follows the framework set forth in *Phillips*.”). Post-issuance procedures include litigation involving infringement and validity before courts and *inter partes* review (IPR), post-grant review (PGR) and covered business method review (CBM) proceedings before the PTAB. See MPEP § 2111 (9th ed. Rev. 10.2019, June 2020). *Inter partes* review is a “trial proceeding conducted at the [PTAB] to review the patentability of one or more claims in a patent only on a ground that could be raised under [35 U.S.C.] §§ 102 or 103, and only on the basis of prior art consisting of patents or printed publications.” *Inter Partes Disputes*, USPTO

claim a broader scope than the *Phillips* standard,<sup>69</sup> “there have been very few decisions in which courts have attributed a variance in claim interpretation to the differences between the two standards.”<sup>70</sup>

Consider a hypothetical claim to obtain a tangible sense of claim scope: A drug for a disease X, consisting of a main structure M, and an element attached to M, wherein the element is A, B, or C. Accordingly, this hypothetical claim covers at most three compounds, i.e., M-A, M-B, and M-C combinations. If the preamble “for disease X” is construed as a limitation,<sup>71</sup> the claim then covers only the ones that are effective for treating disease X among the three possible combinations. The specification is

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(Apr. 2, 2013, 02:39 PM EDT), <https://www.uspto.gov/patents/laws/america-invents-act-ia/inter-partes-disputes#heading-1>. See 37 C.F.R. §§ 42.100–123 (2012) for detailed rules governing *inter partes* review. Post grant review is a “trial proceeding conducted at the [PTAB] to review the patentability of one or more claims in a patent on any ground that could be raised under [35 U.S.C.] § 282(b)(2) or (3).” *Inter Partes Disputes, supra*. See 37 C.F.R. §§ 42.200–224 (2012) for detailed rules governing post grant review. The covered business method review, repealed on September 15, 2020, is a “trial proceeding conducted at the [PTAB] to review the patentability of one or more claims in a covered business method patent.” *Inter Partes Disputes, supra*. See 37 C.F.R. §§ 42.300–304 (2012) for detailed rules governing covered business method review.

69. *Facebook, Inc. v. Pragmatus AV, LLC*, 582 F. App’x 864, 869 (Fed. Cir. 2014) (“The broadest reasonable interpretation of a claim term may be the same as or broader than the construction of a term under the *Phillips* standard. But it cannot be narrower.”).

70. KEVIN GREENLEAF ET AL., INTELL. PROP. OWNERS ASS’N, HOW DIFFERENT ARE THE BROADEST REASONABLE INTERPRETATION AND PHILLIPS CLAIM CONSTRUCTION STANDARDS? 1 (2018).

71. Whether a preamble limits a claim is determined on a case-by-case basis. *See, e.g., Applied Materials, Inc. v. Advanced Semiconductor Materials Am., Inc.*, 98 F.3d 1563, 1572–73 (Fed. Cir. 1996) (“Whether a preamble stating the purpose and context of the invention constitutes a limitation of the claimed process is determined on the facts of each case in light of the overall form of the claim, and the invention as described in the specification and illuminated in the prosecution history.”). It is a settled rule that “a preamble generally is not limiting where a patentee defines a structurally complete invention in the claim body and uses the preamble only to state a purpose or intended use for the invention.” *Catalina Mktg. Int’l, Inc. v. Coolsavings.com, Inc.*, 289 F.3d 801, 808 (Fed. Cir. 2002) (quotation marks omitted). Nevertheless, courts have considered claims similar to the hypothetical claim and acknowledged the preambles were limiting. *E.g., Idenix Pharms. LLC v. Gilead Scis., Inc.*, 941 F.3d 1149, 1155–56 (Fed. Cir. 2019) (interpreting the preamble “[a] method for the treatment of a hepatitis C virus infection” as a narrowing functional limitation because the district court constructed the claim as such and neither party challenged this construction).

then required to provide enough guidance on how to make and use these compounds, including how to synthesize them and determine their efficacy, unless such guidance can be found in the prior art or is within the common knowledge of a PHOSITA.<sup>72</sup> In addition, the necessary experimentation, which is synthesizing and testing the compounds in this example, may not be considered undue experimentation.<sup>73</sup>

Obviously, the more species a claim covers, the more guidance the patentee needs to provide for enablement purposes. The scope of a claim decides how big the set of combinations needs to be enabled, while other factors decide whether the set of combinations is enabled.

#### b. Level of PHOSITA and State of Art

A PHOSITA<sup>74</sup> is a “hypothetical person who is presumed to be aware of all the pertinent prior art.”<sup>75</sup> Section 112(a) requires that the patent document enable “any *person skilled in the art* to which it pertains” to practice the full scope of the claim.<sup>76</sup> Accordingly, the level of a PHOSITA is fundamental in deciding whether a claim is enabled. Factors for determining the level of PHOSITA include: the “type of problems encountered in art; prior art solutions to those problems; rapidity with which innovations are made; sophistication of the technology; and educational level of active workers in the field.”<sup>77</sup> For a given case, it is possible that not all the listed factors are present, and “one or more of them may predominate.”<sup>78</sup>

The state of an art is related to how much a PHOSITA knows about the art. When the art is fairly new, a PHOSITA is considered to have “little or no knowledge independent from the patentee’s instruction”<sup>79</sup> and thus the patentee must provide

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72. See *infra* Section I.A.1.b.

73. See *infra* Section I.A.1.d.

74. Other expressions for the same concept include a person skilled in the art (PSITA), a person of ordinary skills in the art (POSITA), and those skilled in the art.

75. *Custom Accessories, Inc. v. Jeffrey-Allan Indus., Inc.*, 807 F.2d 955, 962 (Fed. Cir. 1986) (citation omitted).

76. 35 U.S.C. § 112(a) (emphasis added).

77. *Custom Accessories*, 807 F.2d at 962.

78. *Id.* at 963.

79. *Chiron Corp. v. Genentech, Inc.*, 363 F.3d 1247, 1254 (Fed. Cir. 2004).

“specific and useful teaching.”<sup>80</sup> In contrast, if the art is mature and a PHOSITA knows how to perform necessary experimentation, then such teaching is not needed and preferably omitted from the specification.<sup>81</sup>

c. Predictability and Nature of Art

Related to, but distinctive from, the state of an art, predictability is about how much can be anticipated from what is known of the art. As explained by the PTO, “[i]f one skilled in the art can readily anticipate the effect of a change within the subject matter to which the claimed invention pertains, then there is predictability in the art.”<sup>82</sup> A PHOSITA’s understanding of an art affects how much can be anticipated from available information. Therefore, the state of an art and the skill level of a PHOSITA provide evidence as to the question of predictability.<sup>83</sup>

Predictability is also closely related to the nature of an art. At one end of the predictability spectrum, a sophisticated mechanical engineer can design a mechanical device and know it will work without actually building it; at the other end, many drugs were discovered by serendipity and chance observations,<sup>84</sup> and pharmaceutical experts can hardly predict what variations can be made to achieve a better effect.<sup>85</sup> Based on such drastic

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80. *Genentech, Inc. v. Novo Nordisk*, A/S, 108 F.3d 1361, 1368 (Fed. Cir. 1997).

81. *Spectra-Physics, Inc. v. Coherent, Inc.*, 827 F.2d 1524, 1534 (Fed. Cir. 1987) (“A patent need not teach, and preferably omits, what is well known in the art.”).

82. MPEP § 2164.03 (9th ed. Rev. 10.2019, June 2020).

83. *Id.*

84. See Pushkar N. Kaul, *Drug Discovery: Past, Present and Future*, in *PROGRESS IN DRUG RESEARCH* 9, 15–16 (Ernst Jucker ed., 1998) (“[T]he overall chronology of new drug discoveries of significance in the 20th century weighs heavily in favor of serendipity and chance observations. A few examples are . . . [c]hlorpromazine, . . . [f]urosemide (Lasix), . . . [and] [c]yclosporine . . . .”); see, e.g., SUSAN ALDRIDGE & JEFFREY L. STURCHIO, *AM. CHEM. SOC’Y & THE ROYAL SOC’Y OF CHEMISTRY, THE DISCOVERY AND DEVELOPMENT OF PENICILLIN 1928–1945*, at 3 (1999) (detailing how the discovery of penicillin began with serendipity).

85. See Kaul, *supra* note 84, at 10 (“New drug discovery from early on involved a trial-and-error approach on naturally derived materials and substances until the end of the nineteenth century.”); see, e.g., *Idenix Pharms. LLC v. Gilead Scis. Inc.*, 941 F.3d 1149, 1155 (Fed. Cir. 2019) (“[I]n the nucleoside area[, a specific type of chemicals,] . . . the smallest change can have a dramatic effect not only on the activity of that compound but on the toxicity

differences in predictability, courts generally treat mechanical and electrical engineering as predictable arts, and chemistry and biology as unpredictable arts.<sup>86</sup>

Predictability is of critical importance when determining whether a claim satisfies the enablement requirement. As stated above, the *Fisher* court has established a “quantitative” relationship between the degree of predictability and the enablement effect: “[T]he scope of enablement . . . varies inversely with the degree of unpredictability of the factors involved.”<sup>87</sup> Predictability also makes a “qualitative” difference for the question of whether a genus claim can be enabled by one single embodiment: “In mechanical cases, . . . broad claims may be supported by a single form of the apparatus disclosed in an applicant’s application,”<sup>88</sup> but “in chemical cases, where an applicant [disclosed only one material], he is not entitled to broader claims than for the material originally disclosed.”<sup>89</sup>

#### d. Quantity and Routineness of Experimentation

According to the *Wands* court, while a large quantity of necessary experimentation does tip the scale towards the undue experimentation side, it may be defeated “if [the experimentation] is merely routine, or if the specification in question provides a reasonable amount of guidance with respect to the direction in which the experimentation should proceed.”<sup>90</sup> When determining the routineness of experimentation, courts usually consider time and difficulty of the experimentation, success and failure of past attempts, and the skill level of a PHOSITA.<sup>91</sup>

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of the compound. So nothing is predictable.” (quotation mark omitted) (citation omitted)).

86. *In re Fisher*, 427 F.2d 833, 839 (C.C.P.A. 1970).

87. *Id.* (emphasis added).

88. *In re Vickers*, 141 F.2d 522, 526–27 (C.C.P.A. 1944).

89. *In re Soll*, 97 F.2d 623, 624 (C.C.P.A. 1938); *see also* MPEP § 2164.03 (9th ed. Rev. 10.2019, June 2020) (“A single embodiment may provide broad enablement in cases involving predictable factors, such as mechanical or electrical elements. However, in applications directed to inventions in arts where the results are unpredictable, the disclosure of a single species usually does not provide an adequate basis to support generic claims.” (citations omitted)).

90. *In re Wands*, 858 F.2d 731, 737 (Fed. Cir. 1988).

91. *See, e.g., ALZA Corp. v. Andrx Pharms., LLC*, 603 F.3d 935, 941–43 (Fed. Cir. 2010).

Nevertheless, about a decade after the *Wands* decision, the Federal Circuit further added that routine experimentation must also be of a reasonable amount.<sup>92</sup> Nowadays, courts have repeatedly determined claims that require large quantities of routine experimentations to be non-enabled.<sup>93</sup>

#### e. Guidance and Examples

As discussed above, the necessary amount of guidance depends on the scope of claim, the state of art, the skill level of a PHOSITA, the nature of art, and predictability.<sup>94</sup> Guidance may be in the form of general principles, but it is more often provided by specific examples of how the invention is practiced. “An example may be ‘working’ or ‘prophetic,’” where the former “is based on work actually performed,” and the latter is “based on predicted results.”<sup>95</sup> Of note, “[u]se of prophetic examples . . . does not automatically make a patent non-enabling.”<sup>96</sup> When the prophetic examples are reasonably reliable, they can also contribute to enablement.<sup>97</sup>

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92. *Enzo Biochem, Inc. v. Calgene, Inc.*, 188 F.3d 1362, 1371 (Fed. Cir. 1999) (“We have held that a patent specification complies with the statute even if a ‘reasonable’ amount of routine experimentation is required in order to practice a claimed invention, but that such experimentation must not be ‘undue.’” (citation omitted)); *Wyeth & Cordis Corp. v. Abbott Lab’ys*, 720 F.3d 1380, 1386 (Fed. Cir. 2013) (“[R]outine experimentation is ‘not without bounds.’” (citation omitted)).

93. *See Wyeth*, 720 F.3d at 1385 (holding that “having to synthesize and screen each of at least tens of thousands of candidate compounds constitutes undue experimentation,” even though “one of ordinary skill could routinely use the assays disclosed in the specification to determine immunosuppressive and antirestenotic effects in candidate compounds”); *see also Idenix Pharms. LLC v. Gilead Scis. Inc.*, 941 F.3d 1149, 1162 (Fed. Cir. 2019) (“Weighing each of these factors, we conclude as a matter of law that the [patent at issue] is invalid for lack of enablement. As described above, a reasonable jury could only have found that at least many, many thousands of [species] meet the structural limitations of [the claim at issue], not all of which [meet the functional limitation].”).

94. *See supra* Sections I.A.1.a–c.

95. MPEP § 2164.02 (9th ed. Rev. 10.2019, June 2020).

96. *Atlas Powder Co. v. E.I. du Pont de Nemours & Co.*, 750 F.2d 1569, 1577 (Fed. Cir. 1984).

97. *Id.* (“[T]he ‘prophetic’ examples of the specification were based on actual experiments that were slightly modified in the patent to reflect what the inventor believed to be optimum, and hence, they would be helpful in enabling someone to make the invention.”).

## 2. Relationship with Utility Requirement

A claim may also fail the enablement requirement as a result of failing the utility requirement under 35 U.S.C. § 101.<sup>98</sup> The logic is straightforward: “[I]f a claimed invention does not have utility, the specification cannot enable one to use it.”<sup>99</sup>

The utility requirement is usually a low bar.<sup>100</sup> An invention has a utility if: (1) a specific and substantial use is apparent or identified by the patentee; and (2) the invention is operative.<sup>101</sup>

A utility is specific if the utility is “particular to the subject matter claimed”<sup>102</sup> and “can be used to provide a well-defined and particular benefit to the public.”<sup>103</sup> For example, in *In re Fisher*, a claim reciting “expressed sequence tags” (ESTs) for encoding certain maize protein fragments was found not to have specific utility because all the seven utilities identified by the applicants were related to general ESTs and not specific to the ESTs claimed.<sup>104</sup> As another example, in *In re Kirk*, the claimed compounds were said to have a “biological activity,” but the exact biological activity was not specified.<sup>105</sup> Such use was also rejected as not specific.<sup>106</sup>

A claim has a substantial utility only if the “claimed invention has a significant and presently available benefit to the public.”<sup>107</sup> For example, a process for producing a compound of no known use is not of a substantial utility.<sup>108</sup> As the court

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98. “Whoever invents or discovers any new and *useful* process, machine, manufacture, or composition of matter, or any new and *useful* improvement thereof, may obtain a patent therefor . . .” 35 U.S.C. § 101 (emphasis added).

99. *In re Brana*, 51 F.3d 1560, 1564 (Fed. Cir. 1995).

100. See *Brooktree Corp. v. Advanced Micro Devices, Inc.*, 977 F.2d 1555, 1571 (Fed. Cir. 1992) (“To violate [35 U.S.C.] § 101 the claimed device must be totally incapable of achieving a useful result.”); see also *E.I. du Pont de Nemours & Co. v. Berkley & Co.*, 620 F.2d 1247, 1260 n.17 (8th Cir. 1980) (“A small degree of utility is sufficient. The claimed invention must only be capable of performing some beneficial function.”(citation omitted)).

101. *E.I. du Pont de Nemours*, 620 F.2d at 1260 n.17.

102. *In re Fisher*, 421 F.3d 1365, 1372 (Fed. Cir. 2005) (citing MPEP § 2107.01).

103. *Id.* at 1371.

104. *Id.* at 1368, 1373.

105. *In re Kirk*, 376 F.2d 936, 938 (C.C.P.A. 1967).

106. *Id.* at 941.

107. *Fisher*, 421 F.3d at 1371.

108. See *Brenner v. Manson*, 383 U.S. 519, 532–36 (1966) (holding that a process for making a steroid of no known use did not satisfy the utility requirement).

recognized, the compound might be found of significant use in the future,<sup>109</sup> but a substantial utility requires a “presently available benefit.”<sup>110</sup> Of particular relevance to this Note, regarding an invention for treating pathological conditions in a human body, its therapeutic effects shown in *in vitro* and/or animal testing are sufficient to support a substantial utility if “there exists a satisfactory correlation” between the *in vitro* and/or animal testing results and the effects observed in humans.<sup>111</sup>

Lastly, an invention is operative if it works for its intended use.<sup>112</sup> The mere existence of inoperative embodiments within the scope of a claim does not necessarily result in the claim failing the utility requirement or being non-enabled.<sup>113</sup> The standard is whether a PHOSITA, in view of the specification, can clearly identify the operative embodiments that fall within the claim scope without undue experimentation.<sup>114</sup>

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109. *Id.* at 535–36 (“This is not to say that we mean to disparage the importance of contributions to the fund of scientific information short of the invention of something ‘useful,’ or that we are blind to the prospect that what now seems without ‘use’ may tomorrow command the grateful attention of the public.”).

110. *Fisher*, 421 F.3d at 1371.

111. *Rey-Bellet v. Engelhardt*, 493 F.2d 1380, 1384 (C.C.P.A. 1974); *see also Ex parte Maas*, No. 86-0178, 1987 WL 123900, at \*3 (B.P.A.I. May 19, 1987); *Ex parte Balzarini*, No. 91-0958, 1991 WL 332576 (B.P.A.I. Mar. 21, 1991).

112. *See E.I. du Pont de Nemours & Co. v. Berkley & Co.*, 620 F.2d 1247, 1260 n.17 (8th Cir. 1980) (“An invention does not lack utility merely because the particular embodiment disclosed in the patent lacks perfection or performs crudely. A commercially successful product is not required. Nor is it essential that the invention accomplish all its intended functions or operate under all conditions, partial success being sufficient to demonstrate patentable utility. In short, the defense of non-utility cannot be sustained without proof of total incapacity.” (citations omitted)).

113. *Atlas Powder Co. v. E.I. du Pont de Nemours & Co.*, 750 F.2d 1569, 1576 (Fed. Cir. 1984) (“Even if some of the claimed combinations were inoperative, the claims are not necessarily invalid.”).

114. *See* MPEP § 2164.08(b) (9th ed. Rev. 10.2019, June 2020) (“However, claims reading on significant numbers of inoperative embodiments would render claims non-enabled when the specification does not clearly identify the operative embodiments and undue experimentation is involved in determining those that are operative.” (citing *Atlas Powder*, 750 F.2d at 1577)).

## B. WRITTEN DESCRIPTION REQUIREMENT

The written description requirement under 35 U.S.C. § 112 has “significant overlap” with the enablement requirement,<sup>115</sup> yet they are “separate and distinct.”<sup>116</sup> The written description requirement serves two policy goals: (1) convey to the public what the patentee claims as the invention; and (2) “demonstrate that the patentee was in possession of the invention that is claimed.”<sup>117</sup> Practically, both the enablement and written description requirements police patent claims from overreaching: The enablement requirement makes sure that a patentee is not able to claim more than she has enabled the public to practice, and the written description requirement guarantees that a patentee does not exclude more than she has actually invented.<sup>118</sup> To demonstrate this point, consider the facts in *Schriber-Schroth*<sup>119</sup> as an example. The patentee claimed a piston comprising a web, and the claim did not recite any limitation regarding the rigidity of the web.<sup>120</sup> The specification, however, described only pistons comprising “extremely rigid” webs.<sup>121</sup> The change of rigidity of the web component might necessitate changes of the other components of the piston or even the overall structure.<sup>122</sup> Responding to the

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115. *Univ. of Rochester v. G.D. Searle & Co.*, 358 F.3d 916, 921 (Fed. Cir. 2004).

116. *Ariad Pharms., Inc. v. Eli Lilly & Co.*, 598 F.3d 1336, 1344 (Fed. Cir. 2010) (“We . . . hold that § 112, first paragraph, contains two separate description requirements: a ‘written description [i] of the invention, and [ii] of the manner and process of making and using [the invention].’ (alteration in original) (citation omitted)).

117. *Capon v. Eshhar*, 418 F.3d 1349, 1357 (Fed. Cir. 2005).

118. See MPEP §§ 2163.I, 2164 (9th ed. Rev. 10.2019, June 2020). The written description requirement also polices claims filed with improper timing, which is not the focus of this Section and thus briefly explained in this footnote. During the patent application process, the applicant may amend the application, including adding new features to claims. When the amended claims are not supported by the original filed specification, the claims fail the written description requirement. Similarly, when the applicant files a continuation application, the original specification might also fail to support the newly filed claims. See MPEP § 2163.I (9th ed. Rev. 10.2019, June 2020) for a comprehensive introduction of failing the written description requirement due to improper timing.

119. *Schriber-Schroth Co. v. Cleveland Tr. Co.*, 305 U.S. 47 (1938).

120. *Id.* at 54–55.

121. *Id.* at 55.

122. *Id.* at 59 (“Inherent flexibility of the web . . . cannot be depended upon to produce the desired effect . . . . As [patentee’s] own expert testified, that

patentee's argument that a PHOSITA would be able to adapt the piston with a flexible web, the United States Supreme Court stated, "[e]ven if those skilled in the art would have known [how to make such adaptations], that was not the invention which [the patentee] described by his references to an extremely rigid web."<sup>123</sup>

Nevertheless, courts have also acknowledged that "there is little difference in some fields between describing an invention and enabling one to make and use it," but that is rarely the case for inventions in unpredictable arts.<sup>124</sup> Indeed, it is a repeated theme in chemical and biological patents that the genus claim may have been enabled, but it is nevertheless insufficiently described.<sup>125</sup>

When evaluating the adequacy of the description for a genus claim, courts consider factors similar to the *Wands* factors, namely, "the existing knowledge in the particular field, the extent and content of the prior art, the maturity of the science or technology, [and] the predictability of the aspect at issue."<sup>126</sup> Ultimately, the test is whether the description allows a PHOSITA to "visualize or recognize the members of the genus."<sup>127</sup> Any form of description is allowed as long as this test is passed, including providing "a precise definition, such as by structure, formula, chemical name, physical properties, or other properties[] of . . . the genus,"<sup>128</sup> claiming by function<sup>129</sup> if "the art has established a correlation between structure and

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depends upon design of the web, with correct proportioning of the different parts as to location and thickness to produce lateral flexibility.").

123. *Id.* at 58–59.

124. *Ariad Pharms., Inc. v. Eli Lilly & Co.*, 598 F.3d 1336, 1352 (Fed. Cir. 2010).

125. *In re DiLeone*, 436 F.2d 1404, 1405 (C.C.P.A. 1971) ("[I]t is possible for a specification to enable the practice of an invention as broadly as it is claimed, and still not describe that invention."); *see, e.g., Ex parte Kubin*, No. 2007-0819, 2007 WL 2070495 (B.P.A.I. May 31, 2007) (reversing the enablement rejection but affirming the written description rejection).

126. *Capon v. Eshhar*, 418 F.3d 1349, 1359 (Fed. Cir. 2005).

127. *Eli Lilly*, 598 F.3d at 1350 (quotation marks omitted).

128. *Id.*

129. Claiming by function, in contrast to claiming by structure, is to claim an invention "by what it does rather than by what it is." *In re Swinehart*, 439 F.2d 210, 212 (C.C.P.A. 1971). For example, if the preamble "a drug for disease X" of the hypothetical claim in *supra* Section I.A.1.a, then this preamble is a functional limitation, and the claim covers only the species that show some effectiveness to disease X.

function,”<sup>130</sup> and listing “a representative number of species falling within the scope of the genus or structural features common to the members of the genus.”<sup>131</sup>

#### 1. Description by Listing “a Representative Number of Species”<sup>132</sup>

Describing a claim by listing “a representative number of species”<sup>133</sup> is most often used when the structure and function relationship is not completely understood. It has also invited a myriad of written description-related litigation.<sup>134</sup> Courts have refused to specify how many species constitute a representative number because “this number necessarily changes with each invention.”<sup>135</sup> Nevertheless, as illustrated below, both logic and relevant cases support the proposition that in order to list “a representative number of species,”<sup>136</sup> the key resides in the representativeness of the listed species rather than the number itself.

Logically, to allow a PHOSITA to visualize the members of a genus by describing a representative number of species, the described species should bear a considerable similarity to undescribed species and be sufficiently diverse so as to represent a substantial portion of different species.<sup>137</sup> For example, consider a hypothetical scenario where one-hundred compounds are covered by a claim. Among the one-hundred compounds, ten compounds comprise main structure M1, and ninety comprise main structure M2. A description of all ten compounds of main structure M1 is not a sufficient description of the claim because the described compounds cannot represent the ones of main structure M2. In contrast, a description of one compound of main structure M1 and one of M2 may be a sufficient disclosure for

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130. *Eli Lilly*, 598 F.3d at 1350.

131. *Id.*

132. *Id.*

133. *Id.*

134. *See, e.g.*, *Regents of the Univ. of Cal. v. Eli Lilly & Co.*, 119 F.3d 1559 (Fed. Cir. 1997); *Invitrogen Corp. v. Clontech Lab’ys, Inc.*, 429 F.3d 1052 (Fed. Cir. 2005); *Juno Therapeutics, Inc. v. Kite Pharma, Inc.*, 10 F.4th 1330 (Fed. Cir. 2021).

135. *Eli Lilly*, 598 F.3d at 1351.

136. *Id.* at 1350.

137. This logical inference is inspired by the standard for representativeness of data in AI development. *See infra* note 163 and accompanying text.

the claim if the described ones can each represent the other compounds of their kinds.

Cases before the PTO and courts are consistent with this logical inference. For example, in *Ex parte Kubin*, the challenged claim was directed to “a genus of polynucleotides encoding polypeptides at least 80% identical to amino acids 22-221 of SEQ ID NO:2 which bind to CD48.”<sup>138</sup> The applicant listed five sequences that fell within the scope of this claim.<sup>139</sup> However, observing that “[n]one of these sequences varies amino acids 22-221,” the Board held the listed sequences were “not representative of the genus.”<sup>140</sup> In other words, the described species were not sufficiently diverse because they failed to represent the species that are less than 100% identical to amino acids 22-221, which account for a portion—perhaps a major portion—of the whole claimed genus. Another example is *Invitrogen Corp. v. Clontech Laboratories, Inc.*, where the claim at issue recited, “[a]n isolated polypeptide . . . encoded by a modified reverse transcriptase [‘RT’] nucleotide sequence . . . , wherein said nucleotide sequence is derived from . . . a retrovirus, yeast, Neurospora, Drosophila, primates [or] rodents.”<sup>141</sup> In the specification, the patentee described two nucleotide sequences (also known as DNA or genes) and referred to eight publications for providing the nucleotide sequences derived from five different retroviruses, three different yeasts, and some primates and rodents.<sup>142</sup> Moreover, the court found that “members of the RT gene family shared significant homologies from one species of RT to another.”<sup>143</sup> Accordingly, in this case, the species were similar to some of the others, and the described species were diverse enough to cover each type of claimed species. Although the court did not explicitly provide this line of reasoning, it held the patent satisfied the written description requirement after stating the cited facts.<sup>144</sup>

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138. *Ex parte Kubin*, No. 2007-0819, 2007 WL 2070495, at \*9 (B.P.A.I. May 31, 2007) (quotation marks omitted).

139. *Id.* (“In this case, Appellants have sequenced two nucleic acids falling within the scope of claim 73 and three fusion proteins whose nucleotide sequences would fall within the scope of claim 73.”).

140. *Id.*

141. *Invitrogen Corp. v. Clontech Lab’s, Inc.*, 429 F.3d 1052, 1072 (Fed. Cir. 2005) (citing U.S. Patent No. 6,063,608, col. 19 ll. 26–34 (filed Feb. 10, 1997)).

142. U.S. Patent. No. 6,063,608 col. 9 ll. 34–47 (filed Feb. 10, 1997).

143. *Invitrogen*, 429 F.3d at 1073.

144. *Id.* at 1073–74.

Of course, if the number of listed species is too small, the listed species will not be diverse enough to represent the claimed genus, which is what happened in *Ariad v. Eli Lilly* (no concrete examples presented),<sup>145</sup> *UC v. Eli Lilly* (describing rat insulin cDNA only while claiming genus of vertebrate and mammalian insulin cDNA),<sup>146</sup> and *Juno v. Kite* (describing two examples of binding elements that bind to two targets, respectively, but claiming binding elements without limiting the targets).<sup>147</sup>

A representativeness issue may also arise when too many listed examples are not within the scope of the genus claim such that a PHOSITA cannot “visualize or recognize the members of the genus.”<sup>148</sup> After all, an example that is not a species of a claimed genus cannot represent those that are. Therefore, providing a “laundry list” of all possible species will not help satisfy the written description requirement.<sup>149</sup> A stronger caveat to the “laundry list” practice is that if the accused species is not included in the list, it will be extremely difficult for the patentee to convince a jury that she is in possession of this species.<sup>150</sup>

## II. AI'S POWER IN PREDICTING “UNPREDICTABLE” ARTS

While genus claims in the unpredictable arts are having a hard time meeting the enablement and written description

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145. *Ariad Pharms., Inc. v. Eli Lilly & Co.*, 598 F.3d 1336, 1357–58 (Fed. Cir. 2010) (“The . . . patent discloses no working or even prophetic examples of [the claimed method] . . .”).

146. *Regents of the Univ. of Cal. v. Eli Lilly & Co.*, 119 F.3d 1559, 1568 (Fed. Cir. 1997) (“[A] description of rat insulin cDNA is not a description of the broad classes of vertebrate or mammalian insulin cDNA.”).

147. *Juno Therapeutics, Inc. v. Kite Pharma, Inc.*, 10 F.4th 1330, 1337 (Fed. Cir. 2021) (“The disclosure of one scFv [i.e., single-chain antibody variable fragment, a type of binding element,] that binds to CD19 and one scFv that binds to a PSMA antigen on prostate cancer cells in the manner provided in this patent does not provide information sufficient to establish that a skilled artisan would understand how to identify the species of scFvs capable of binding to the limitless number of targets as the claims require.”).

148. *Eli Lilly*, 598 F.3d at 1350 (quotation marks omitted).

149. *See Fujikawa v. Wattanasin*, 93 F.3d 1559, 1571 (Fed. Cir. 1996) (“[S]imply describing a large genus of compounds is not sufficient to satisfy the written description requirement as to particular species or sub-genuses.”).

150. *See, e.g., Idenix Pharms. LLC v. Gilead Scis. Inc.*, 941 F.3d 1149, 1164 (Fed. Cir. 2019) (“The specification . . . provides no method of distinguishing effective from ineffective compounds for the compounds reaching beyond the formulas disclosed in the . . . patent . . . . In the absence of that guidance, the listed examples and formulas cannot provide adequate written description support for undisclosed nucleosides that also happens to [be effective].”).

requirements,<sup>151</sup> AI techniques have progressed to the point where they are capable of making reasonably accurate predictions for many important problems in these “unpredictable” arts.<sup>152</sup> To properly translate AI’s prediction power into a new patent practice, it is necessary to understand how AI works, how well it works, and its limitations. Before proceeding to these topics, it is worth clarifying that machine learning (ML) is a major portion of currently available AI.<sup>153</sup> Similar to other articles related to AI and ML, hereinafter, this Note uses ML and AI interchangeably.<sup>154</sup>

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151. See *supra* Part I.

152. For the sake of completeness, a pure computation approach based on established scientific principles can also provide predictions in the traditionally unpredictable arts. See Keith T. Butler et al., *Machine Learning for Molecular and Materials Science*, 559 NATURE 547, 547 (2018) (“The field of computational chemistry has become increasingly predictive in the twenty-first century, with activity in applications as wide ranging as catalyst development for greenhouse gas conversion, materials discovery for energy harvesting and storage, and computer-assisted drug design.” (citation omitted)). Although the pure computation approach remains an option for assisting research and development in many industries, AI is more advantageous because: (1) AI requires fewer computational resources, see Angeles Pulido et al., *Functional Materials Discovery Using Energy-Structure-Function Maps*, 543 NATURE 657, 657 (2017) (“Computational prediction of stability and function has great potential . . . but it is difficult in practice because of the computational expense . . . .”); and (2) AI can better handle non-ideal and complex situations, see Marwin H. S. Segler & Mark P. Waller, *Neural-Symbolic Machine Learning for Retrosynthesis and Reaction Prediction*, 23 CHEM. EUR. J. 5966, 5966 (2017) (discussing how the rule-based approach of pure computation “cannot predict anything outside of their knowledge”). Nevertheless, in a scenario where the pure computation approach can make satisfactory predictions, arguments regarding AI application in patent practice in *infra* Part III are generally applicable to the pure computation approach as well.

153. See ETHEM ALPAYDIN, INTRODUCTION TO MACHINE LEARNING 3 (2d ed. 2010) (explaining what machine learning is and providing examples of it).

154. See, e.g., Xin Yang et al., *Concepts of Artificial Intelligence for Computer-Assisted Drug Discovery*, 119 CHEM. REV. 10520, 10521 (2019) (“[W]e will use the term ‘AI’ as a synonym for certain machine learning techniques . . . .”); Lucas B. Ayres et al., *Taking the Leap Between Analytical Chemistry and Artificial Intelligence: A Tutorial Review*, 1161 ANALYTICA CHIMICA ACTA, no. 338403, 2021, at 3 (“[M]ost of the papers discussed in this review do not make an explicit difference between AI and machine learning . . . .”).

## A. AI WORK PRINCIPLES

The basic AI workflow<sup>155</sup> can be briefly summarized as data preparation, model training, and model evaluation and optimization.<sup>156</sup>

### 1. Data Preparation

Data preparation is a non-trivial step in any AI training processes because “it underpins all further progress.”<sup>157</sup> AI performance heavily depends on “the representativeness, quality, and quantity of initial data.”<sup>158</sup>

As the old saying goes, “garbage in, garbage out.”<sup>159</sup> Data quality is critically important for AI development. Unfortunately, “[t]here is no universal approach to verifying the quality of . . . data.”<sup>160</sup> “One needs to understand the origin and meaning of the training data” to eliminate incomplete,

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155. For the reasons below, the AI workflow introduced in this Section is for supervised learning only. Current learning modes can be generally categorized as supervised learning or unsupervised learning. Yang et al., *supra* note 154, at 10525. In supervised learning, the training data includes input values and corresponding output values. Butler et al., *supra* note 152, at 548. The goal of supervised learning is “to derive a function that, given a specific set of input values, predicts the output values to an acceptable degree of fidelity.” *Id.* In unsupervised learning, the training data includes input values only. Yang et al., *supra* note 154, at 10525. The aim of unsupervised learning is “to find the regularities in the input,” ALPAYDIN, *supra* note 153, at 11, such as “trends, patterns or clustering in the data.” Butler et al., *supra* note 152, at 548. Since supervised learning is mostly used when predictions are desired, *see* Yang et al., *supra* note 154, at 10525 (“Many AI learning algorithms use a supervised learning process, . . . and the goal of the training process is to learn a mapping function from the input to the output . . . such that the class labels Y (in case of a classifier) or target values Y (for quantitative output data) for unseen data X can be correctly predicted.” (citation omitted)), this Section introduces the workflow for supervised learning only.

156. *See* ALTUNA AKALIN, COMPUTATIONAL GENOMICS WITH R § 5.2 (2020), <https://compgenomr.github.io/book/> (providing an overview of the steps used in supervised learning).

157. Yang et al., *supra* note 154, at 10536.

158. *Id.*

159. “In computer science, garbage in, garbage out (GIGO) is the concept that flawed, or nonsense (garbage) input data produces nonsense output.” *Garbage in, Garbage out*, WIKIPEDIA, [https://en.wikipedia.org/wiki/Garbage\\_in,\\_garbage\\_out](https://en.wikipedia.org/wiki/Garbage_in,_garbage_out) (last updated June 9, 2022) (emphasis omitted).

160. DAVID J. LILJA, LINEAR REGRESSION USING R: AN INTRODUCTION TO DATA MODELING 7 (1.1 ed. 2017).

abnormal, and otherwise improper data entries to ensure a reasonable data quality.<sup>161</sup>

The other two properties, representativeness and quantity of data, are closely related but different. To ensure the representativeness of data, one needs to confirm that the data populates “the space of possible inputs that [users] might want to make predictions for.”<sup>162</sup> For example, if one desires to predict the weather of Minnesota on a given day, a set of training data that includes the weather of a whole past year possesses a better representativeness than one that includes the weather in winter of several past years. If the latter case happens, AI developers will need to enlarge the quantity of data by accessing more databases, repurposing data from other disciplines, or using some innovative strategies to make the data populate the “unpopulated” problem space.<sup>163</sup>

Additionally, closely related to this Note, data presentation presents more difficulty in chemistry, biology, and materials science than other disciplines due to their complexity.<sup>164</sup> Consider the Minnesota weather example again. If one would like to use Minnesota as a geographical input variable, “MN” means nothing to a computer unless it is associated with its longitude, latitude, and potentially the number of mountains and lakes in it. Compounds need to be represented to a similar effect as well.<sup>165</sup> Nowadays, multiple representations for compounds have been developed, including sequences, fixed-size

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161. Yang et al., *supra* note 154, at 10536.

162. *Id.*

163. Databases and repurposing of data are discussed in *infra* Section II.C. Examples of using innovative strategies to obtain more data include the works of Raccuglia et al., *see infra* Section II.B.3.a, and Segler et al., *see infra* note 271.

164. For example, in computer vision, all pixels can be readily converted to data that represents their corresponding colors. But structures of a molecule cannot be easily transformed to numbers. See Yang et al., *supra* note 154, at 10536–37 for a detailed discussion of different methods for representing molecules and their limitations.

165. The science community has established four requirements for representations of compounds: (1) “Complete: Features of a material relevant to the problem being studied should be captured;” (2) “Descriptive: Similar materials should have similar representations;” (3) “Simple: Computing the representation should be fast;” and (4) “Unique: All materials should have exactly one representation.” Logan Ward & Chris Wolverton, *Atomistic Calculations and Materials Informatics: A Review*, 21 CURRENT OP. SOLID STATE & MATERIALS SCI. 167, 168 (2017).

vectors, and molecular structure graphs.<sup>166</sup> AI developers need “insight into both the underlying scientific problem and the operation of the learning algorithm” to choose the representation that best serves their goals.<sup>167</sup>

In conclusion, the practice of AI developing “is said to consist of at least 80% data processing and cleaning and 20% algorithm application,”<sup>168</sup> and “data preparation is a labor-intensive and challenging task.”<sup>169</sup>

## 2. Model Training

Choosing a model is to assume how input and output data are related.<sup>170</sup> For example, if a model denoted as  $f_{\theta}(\cdot)$  is chosen, denoting input and output as  $x$  and  $y$ , respectively, then it is assumed that  $y = f_{\theta}(x)$ , where  $\theta$  is a set of parameters of the model  $f(\cdot)$ .<sup>171</sup> The training process is to feed the training data to a computer, which comprises a set of  $x$ 's and corresponding  $y$ 's, and then calculate  $\theta$ .<sup>172</sup> After the computer finds an appropriate parameter  $\theta$ , the exact relationship between  $x$  and  $y$ , i.e.,  $f_{\theta}(\cdot)$ , is determined.<sup>173</sup> AI users can then use the trained model to predict the output for new input. For instance, denoting a new input as  $x'$ , then the prediction will be  $y' = f_{\theta}(x')$ .<sup>174</sup>

Accordingly, different models assume different relationships between inputs and outputs, and each has its

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166. Yang et al., *supra* note 154, at 10536–37.

167. Butler et al., *supra* note 152, at 548.

168. Jessica Vamathevan et al., *Applications of Machine Learning in Drug Discovery and Development*, 18 NATURE REVIEWS DRUG DISCOVERY 463, 466 (2019).

169. Yang et al., *supra* note 154, at 10536.

170. See ALPAYDIN, *supra* note 153, at 3–9 (illustrating machine learning processes with examples).

171. To be more concrete, the exact relationship between  $x$  and  $y$  depends on  $f_{\theta}(\cdot)$ , which in turn depends on  $\theta$ . For example, suppose one chooses  $y = f_{\theta}(x) = x + \theta$ . Then if a computer finds  $\theta = 1$  according to the training data, the exact relationship between  $x$  and  $y$  will be  $y = f_{\theta}(x) = x + 1$ . To make predictions, if a new input  $x' = 2$  is given, the computer (now a trained AI) will predict the corresponding output to be  $y' = 2 + 1 = 3$ . Of course, no real AI models are this simple. But the process of training AI and making predictions generally follows this procedure.

172. See ALPAYDIN, *supra* note 153, at 41–42 (illustrating supervised learning processes).

173. See *id.*

174. See *id.* at 5–11 (discussing how parameters are determined in supervised learning processes).

advantages and drawbacks.<sup>175</sup> Moreover, training processes of most models “are not fully autonomous, requiring at least some guidance.”<sup>176</sup> The values of parameters are often “estimated beforehand using systematic and random searches, or heuristics.”<sup>177</sup> Accordingly, expertise and trial-and-error are usually required in an AI training process.<sup>178</sup>

### 3. Model Evaluation and Optimization

After an AI model is trained, one needs to evaluate and usually optimize the trained model before using it for real problems.<sup>179</sup> The key evaluation for AI is its performance on unseen inputs.<sup>180</sup> A widely used method for such evaluation is: (1) randomly withholding a portion of data from being used in the model training process; (2) using the trained model to predict the outputs of the withheld data; and (3) comparing the predicted outputs with the actual outputs.<sup>181</sup> The specific comparison between predicted and actual output depends on whether the AI is a classifier or regressor.<sup>182</sup> Accordingly,

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175. Antonio Lavecchia, *Machine-Learning Approaches in Drug Discovery: Methods and Applications*, 20 DRUG DISCOVERY TODAY 318, 328 tbl. 2 (2015). For example, advantages of the SVM model (used in the work of Raccuglia et al., *infra* note 263) include: it “[d]oes not make any assumption about type of relation between target property and molecular descriptors”; there is “low risk of overfitting”; and it is “able to provide expected classification accuracies for individual compounds.” *Id.* The SVM model’s disadvantages include that it is used for “predominantly binary classification only.” *Id.* Advantages of the Naïve Bayesian model (used in the work of Shi et al., *infra* note 236) include that it is “not sensitive to irrelevant features;” and it “handles real and discrete data,” and its disadvantages include that it “[a]ssumes independence of features.” *Id.*

176. Butler et al., *supra* note 152, at 549.

177. *Id.*

178. *See id.* (“Even modest changes in the values of hyperparameters can improve or impair learning considerably, and the selection of optimal values is often problematic.”).

179. *Id.*

180. *Id.*

181. *Id.* In addition, cross-validation is also a commonly used method for evaluating AI performance. *See* ALPAYDIN, *supra* note 153, at 40.

182. *See* Butler et al., *supra* note 152, at 548. An AI is called a classifier if it performs classification over data. In a classification scenario, the outputs  $y$ ’s are discrete values, such as “hot” or “cold” in the Minnesota weather example. In contrast, in a regression scenario, the outputs  $y$ ’s are continuous values, which can be exact temperatures in the Minnesota weather example. *See, e.g.*, ALPAYDIN, *supra* note 153, at 41 (“[The output] is 0/1 for two-class learning, is a  $K$ -dimensional binary vector (where exactly one of the dimensions is 1 and all others 0) for ( $K > 2$ )-class classification, and is a real value in regression.”).

evaluation for classifiers and regressors are based on different measures.

One of the most common performance measures for classifiers is accuracy.<sup>183</sup> Its definition is straightforward, that is, the number of correct classification predictions divided by the number of total predictions.<sup>184</sup> It ranges from zero to one, where one means the predictions are 100% accurate. Another popular metric for classifiers is the area under the Receiver Operating Characteristic (ROC)<sup>185</sup> curve, known as the "AUC."<sup>186</sup> AUC has become more widely used because it is arguably more consistent<sup>187</sup> and discriminating<sup>188</sup> than accuracy, the aforementioned performance measure.<sup>189</sup> The range of AUC is

183. *E.g.*, Valentin Stanev et al., *Machine Learning Modeling of Superconducting Critical Temperature*, 4 NPJ COMPUTATIONAL MATERIALS, 2018, at 1, 5 (using accuracy as one of the metrics evaluating a classifier).

184. Formally, accuracy is defined as

$$\text{accuracy} = (tp + tn)/(tp + tn + fp + fn)$$

where "tp" means true positive, "tn" true negative, "fp" false positive, and "fn" false negative. *Id.* at 4.

185. "On an ROC graph, [true positive] is plotted on the Y axis and [false positive] is plotted on the X axis. These statistics vary together as a threshold on a classifier's continuous output is varied between its extremes, and the resulting curve is called the ROC curve." Foster Provost & Tom Fawcett, *Analysis and Visualization of Classifier Performance: Comparison Under Imprecise Class and Cost Distributions*, in PROCEEDINGS OF THE THIRD INTERNATIONAL CONFERENCE ON KNOWLEDGE DISCOVERY AND DATA MINING 43, 44 (1997).

186. See ALPAYDIN, *supra* note 153, at 491 ("ROC allows a visual analysis; if we want to reduce the curve to a single number we can do this by calculating the area under the curve (AUC). A classifier ideally has an AUC of 1 and AUC values of different classifiers can be compared to give us a general performance averaged over different loss conditions.").

187. Intuitively, if *f* and *g* are two different measures for evaluating two learning algorithms A and B, *f* and *g* are said to be consistent if "*f* stipulates that algorithm A is (strictly) better than B, then *g* will not say B is better than A." Charles X. Ling et al., *AUC: A Statistically Consistent and More Discriminating Measure Than Accuracy*, in PROCEEDINGS OF THE EIGHTEENTH INTERNATIONAL JOINT CONFERENCE ON ARTIFICIAL INTELLIGENCE 519, 521 (2003). See *id.* for a formal definition of degree of consistency.

188. Intuitively, if *f* and *g* are two different measures for evaluating two learning algorithms A and B, *f* is said to be more discriminating than *g* if there are cases where *f* is able to reflect the difference between the performance of algorithms A and B and *g* is unable to provide such reflection, and not vice versa. *Id.* See *id.* for formal definition of degree of discriminancy.

189. See generally *id.* But see Jorge M. Lobo et al., *AUC: A Misleading Measure of the Performance of Predictive Distribution Models*, 17 GLOB. ECOLOGY & BIOGEOGRAPHY 145 (2008) (questioning AUC's "reliability as a comparative measure of accuracy between model results").

from zero to one, where one means the predictions are 100% accurate, and 0.5 means a 50-50 guess.<sup>190</sup>

Performance measures for regressors are more complicated, diverse, and controversial.<sup>191</sup> Among them, Pearson's correlation coefficient ( $r$ ) or its square ( $r^2$ ), Mean Absolute Error (MAE) and Mean Square Error (MSE) or its equivalent Root Mean Square Error (RMSE) are most commonly used.<sup>192</sup> MAE and RMSE both reflect the average difference between the predicted and actual values.<sup>193</sup> The smaller the MAE and/or MSE/RMSE values, the more accurate the regressor. Nevertheless, the values of MAE and MSE/RMSE depend on the scale of data.<sup>194</sup> Therefore, one can only use these two measures to evaluate AI for similar problems but cannot obtain from them a general sense of how good an AI's performance is. Pearson's correlation coefficient  $r$  and  $r^2$  are "statistical measure[s] of how well the model describes the measured data."<sup>195</sup>  $r$  and  $r^2$  both range from zero to one, and in general, the values that "are closer to one indicate a better-fitting model."<sup>196</sup> Although  $r$  and  $r^2$  are measures of correlation, they "have been used as predictive accuracy measures in various disciplines in numerous studies . . ."<sup>197</sup>

190. Alex J. Bowers & Xiaoliang Zhou, *Receiver Operating Characteristic (ROC) Area Under the Curve (AUC): A Diagnostic Measure for Evaluating the Accuracy of Predictors of Education Outcomes*, 24 J. EDUC. FOR STUDENTS PLACED RISK 20, 22 (2019).

191. See Alexei Botchkarev, *A New Typology Design of Performance Metrics to Measure Errors in Machine Learning Regression Algorithms*, 14 INTERDISC. J. INFO., KNOWLEDGE, & MGMT. 45, 46 (2019) (summarizing more than forty different metrics for regression models).

192. Jin Li, *Assessing the Accuracy of Predictive Models for Numerical Data: Not  $r$  nor  $r^2$ , Why Not? Then What?*, 12 PLoS ONE, no. 8, 2017, at 12 ("Of [the measures for regressors], besides  $r$  and  $r^2$ , MAE and root MSE (RMSE) are among the most commonly used or recommended measures." (citation omitted)).

193. Mathematically, MAE is given by

$$\text{MAE} = \sum_i |y_i - \hat{y}_i| / n$$

and RMSE is given by

$$\text{RMSE} = (\sum_i (y_i - \hat{y}_i)^2 / n)^{1/2}$$

where  $\hat{y}_i$  is the predicted output value corresponding input  $x_i$ , and  $y_i$  is the actual output value corresponding to  $x_i$ . Botchkarev, *supra* note 191, at 61 tbl. 3 (displaying definitions of various metrics for regressors). Accordingly, the absolute error of the  $i$ -th prediction is given by  $|y_i - \hat{y}_i|$ , and the average and squared average of errors are reflected by MAE and RMSE, respectively.

194. Li, *supra* note 192, at tbl. 2 (showing that MAE and MSE/RMSE are not scale-independent).

195. LILJA, *supra* note 160, at 23.

196. *Id.* at 23-24.

197. Li, *supra* note 192, at 1-2.

Since  $r$  and  $r^2$  are scale-independent, in contrast with MAE and RMSE, this Note uses  $r$  or  $r^2$  as performance measures for regressors in the next Section.

The AI developing process is not a one-time job.<sup>198</sup> One needs to evaluate and optimize the AI several times by adjusting the parameters of the model, modifying the learning algorithm, and/or improving the quantity and quality of training data until the AI reaches satisfactory performance.<sup>199</sup>

## B. AI APPLICATION IN DRUG DISCOVERY

The traditionally unpredictable arts, including chemistry and biology, usually contribute “unpredictable factors”<sup>200</sup> to material and drug inventions.<sup>201</sup> Although materials and drugs are apples and oranges with respect to their technological details, AI predictions in these two areas do not exhibit qualitative differences. In short, AI is showing great performance in predicting structures and properties for materials<sup>202</sup> and making considerable contribution to the discovery of new materials.<sup>203</sup> Hundreds of AI-related papers in

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198. See Yang et al., *supra* note 154, at 10537 fig. 14 (displaying a process for developing and improving AI).

199. *Id.*

200. *In re Fisher*, 427 F.2d 833, 839 (C.C.P.A. 1970).

201. *E.g.*, U.S. Patent No. 10,161,021 (filed Apr. 20, 2017); U.S. Patent No. 7,608,597 (filed June 20, 2003).

202. *E.g.*, Stanev et al., *supra* note 183, at 6 (presenting an AI that was able to predict superconducting temperatures of known superconducting materials with a correlation coefficient of 0.88, and some common features of materials with high superconducting temperatures were extracted and more superconducting materials were discovered based on the predictions); Jerome G. P. Wicker & Richard I. Cooper, *Will It Crystallize? Predicting Crystallinity of Molecular Materials*, 17 CRYSTENGCOMM 1927, 1930 (2015) (showing an AI that achieved an accuracy of 90.3% in predicting whether sets of drug-like compounds would crystallize, and conditions affecting the crystallization tendency were found with the aid of AI); Rahman Sabouhi et al., *Measuring the Mechanical Properties of Polymer-Carbon Nanotube Composites by Artificial Intelligence*, 25 INT'L J. DAMAGE MECHS. 538, 553 (2016) (providing an AI that was able to predict the depth-sensing indentation (DSI, an important mechanical property for materials) of Polymer-Carbon nanotube composites with a  $r^2$  score of 0.98, and claiming this AI would be a satisfying alternative to conventional experiment measurement of DSI).

203. See, *e.g.*, Pulido et al., *supra* note 152, at 657 (providing an energy-structure-function map created by AI, several ultra-high-porous materials with great gas adsorption potentials were identified including one that has been experimentally confirmed to be the lowest density of any molecular organic crystals known to date); Bryce Meredig et al., *Combinatorial Screening for New*

materials science have been published every year since 2015, and the number keeps growing fast.<sup>204</sup> Accordingly, arguments regarding AI applications in drug-related inventions are equally applicable to material-related inventions.

Drug discovery is “the process of discovering new candidate medications.”<sup>205</sup> The research and development (R&D) of a new drug has always been “a very expensive and time-consuming process.”<sup>206</sup> “[T]he cost of developing a new prescription medicine that gains marketing approval is estimated to cost \$2,558 million,” and the process “often lasts more than a decade.”<sup>207</sup> Fortunately, the rational, computation-based (including AI-based) approach is more efficient than the traditional way of drug discovery.<sup>208</sup> Indeed, many AI-driven biopharmaceutical companies, including Pharnext, Lantern Pharma, Healx, and Innoplexus “have been committed to the development of drug combinations based on [machine learning] and network pharmacology methods.”<sup>209</sup> The examples below account for just a tiny portion of all available publications given the fact that typically fifty to around one-hundred papers related to AI-

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*Materials in Unconstrained Composition Space with Machine Learning*, 89 PHYSICAL REV. B, no. 9, 2014, at 094104-1, 094104-1, 094104-4 (providing AI that was able to scan “millions to even trillions of candidate [ternary compounds] in reasonable time” and predict their formation energies with an  $r^2$  score above 0.9, from which 4500 new stable ternary compounds were proposed); Piyush M. Tagade et al., *Attribute Driven Inverse Materials Design Using Deep Learning Bayesian Framework*, 5 NPJ COMPUTATIONAL MATERIALS, 2019, at 1 (presenting an approach of discovering materials from desired properties by AI, which was claimed to be a general approach that can be used to find organic semiconductors for thin-film transistors, small organic acceptors for solar cells and electrolyte additives with high redox stability, and inorganic materials as well).

204. Dane Morgan & Ryan Jacobs, *Opportunities and Challenges for Machine Learning in Materials Science*, 50 ANN. REV. MATERIALS RSCH. 71, 73 fig. 1 (2020).

205. Natalie Stephenson et al., *Survey of Machine Learning Techniques in Drug Discovery*, 20 CURRENT DRUG METABOLISM 185, 185 (2019).

206. *Id.*

207. *Id.*

208. Evanthia Lionta et al., *Structure-Based Virtual Screening for Drug Discovery: Principles, Applications and Recent Advances*, 14 CURRENT TOPICS MED. CHEMISTRY 1923, 1923 (2014).

209. Lianlian Wu et al., *Machine Learning Methods, Databases and Tools for Drug Combination Prediction*, 23 BRIEFINGS BIOINFORMATICS, 2021, at 1, 16; see also Stephenson et al., *supra* note 205, at 188, 191 tbl. 2 (listing startup companies that “are actively pioneering in the drug and medication discovery and development field using AI techniques”).

assisted drug discovery have been published every year since 2005.<sup>210</sup> Nevertheless, these examples show AI's great power to facilitate diverse aspects of R&D in the drug industry, and particularly, with the aid of AI, the predictability of the traditionally unpredictable arts is much higher than "drilling for oil."<sup>211</sup>

### 1. Virtual Screen and Property Prediction

The identification of lead compounds,<sup>212</sup> i.e., promising drug prospects that show pharmacological activity against a biological target, is at the center of early-stage drug detection.<sup>213</sup> This step is conventionally performed by "experimental screening of large libraries of chemicals against a therapeutically-relevant target."<sup>214</sup> Thanks to the development of computation<sup>215</sup> and AI techniques, the screening can now be performed virtually (the so-called "virtual screen").<sup>216</sup> In addition to predicting potency of drug candidates, AI can also assist scientists to virtually screen other drug properties, including absorption,<sup>217</sup> distribution,<sup>218</sup>

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210. Stephenson et al., *supra* note 205, at 189 fig. (2).

211. *Enzo Biochem, Inc. v. Calgene, Inc.*, 188 F.3d 1362, 1372 (Fed. Cir. 1999) (noting that the district court analogized the predictability of antisense, a specific biological mechanism, to "drilling for oil").

212. A lead compound is "a drug-like small molecule . . . that will progress into preclinical, and if successful, into clinical development and ultimately be a marketed medicine." J. P. Hughes et al., *Principles of Early Drug Discovery*, 162 BRIT. J. PHARMACOLOGY 1239, 1239 (2011) (citation omitted).

213. Lionta et al., *supra* note 208, at 1923.

214. *Id.*

215. *See supra* note 152 (introducing briefly the applications of computation in the traditionally unpredictable arts).

216. Lionta et al., *supra* note 208; Yang et al., *supra* note 154, at 10538.

217. Drug absorption is the process by which "drug molecules are absorbed into the bloodstream from the absorption site through one or more biological membrane barriers." Yang et al., *supra* note 154, at 10558.

218. "Distribution is the process by which drug molecules diffuse or are actively transported from the bloodstream to body tissues, particularly the tissue(s) where the action is expected to occur." *Id.* at 10558–59.

metabolism,<sup>219</sup> excretion,<sup>220</sup> and toxicity<sup>221</sup> (collectively, ADMET).<sup>222</sup>

*Binding affinity.*<sup>223</sup> Usually, a drug's effect begins when it binds itself to a biomolecular target.<sup>224</sup> Hence, binding affinity is a good indication of a compound's potential against certain diseases.<sup>225</sup> Zilian & Sottriffer used experimentally confirmed

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219. Metabolism, in this context, is the chemical transformation of drugs inside the human body. *Id.* at 10559.

220. "Drug excretion is the process of removing drug molecules from the body . . ." *Id.* at 10561.

221. "Drug toxicity refers to the adverse effect on an organism or a substructure of the organism (e.g., cells and organs) due to the action or metabolism of a compound." *Id.*

222. *Id.* at 10573.

223. "[B]inding affinity is the strength of the interaction between two (or more than two) molecules that bind reversibly (interact)." Panagiotis L. Kastritis & Alexandre M. J. J. Bonvin, *On the Binding Affinity of Macromolecular Interactions: Daring to Ask Why Proteins Interact*, 10 J. ROYAL SOC'Y INTERFACE, no. 79, 2013, at 6.

224. See TERRENCE P. KENAKIN, A PHARMACOLOGY PRIMER: THEORY, APPLICATIONS, AND METHODS 2 (3d ed. 2009) ("[A]s a prerequisite to exerting an effect, all drug molecules must bind to and interact with receptors.").

225. Binding affinity is closely correlated to drug potency for "antagonists," but not for "agonists." *Id.* at 81–82 ("There are . . . differences between binding and functional experiments . . . . No differences should be seen for antagonists . . . . The complex interplay between affinity and efficacy can be misleading in structure activity studies for agonists."). An "antagonist" is "a pharmacologically active molecule that blocks physiological effect," which exerts no effects other than blocking the target site. *Id.* at 9. In contrast, an "agonist" is "a molecule [that] binds to a receptor and produces its own effect . . ." *Id.* Accordingly, the drug potency of an antagonist only depends on its binding affinity, while the drug potency of an agonist depends on both the binding affinity and its efficacy. Efficacy is "[t]he property that gives a molecule the ability to change a receptor, such that it produces a cellular response . . ." *Id.* at 14. Nevertheless, in either case, knowing the binding affinity of drug candidates helps narrow the searching scope and is a good starting point for virtual screening.

binding affinity data sets<sup>226</sup> to train a regression-based<sup>227</sup> random forest (RF) model,<sup>228</sup> and achieved a Pearson's correlation coefficient<sup>229</sup> up to 0.779 between the experimentally measured and predicted binding affinity values.<sup>230</sup> This is significantly higher than the best predictions made by traditional computation approaches, where the best correlation coefficient is around 0.6.<sup>231</sup>

*Pregnane X receptor*<sup>232</sup> *activator*. The activation of the pregnane X receptor (PXR) by drugs may have a "substantial impact on drug metabolism, transportation, and drug-drug interactions."<sup>233</sup> Accordingly, knowing whether a drug candidate

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226. Two types of datasets were used in the study: PDBbind and CSAR. David Zilian & Christoph A. Sotriffer, *SFCscoreRF: A Random Forest-Based Scoring Function for Improved Affinity Prediction of Protein-Ligand Complexes*, 53 J. CHEM. INFO. & MODELING 1923, 1924 (2013). Zilian & Sotriffer referred to the PDBbind dataset as "generic" or "benchmark." *Id.* The PDBbind dataset includes binding affinity values of 1622 protein-ligand complexes, 900 of which are particularly valuable for docking and scoring studies. Renxiao Wang et al., *The PDBbind Database: Methodologies and Updates*, 48 J. MED. CHEMISTRY 4111, 4111 (2005). CSAR dataset is 343 protein-ligand complexes with binding affinity data. See Richard D. Smith et al., *CSAR Benchmark Exercise of 2010: Combined Evaluation Across All Submitted Scoring Functions*, 51 J. CHEM. INFO. & MODELING 2115, 2116 (2011) ("In this analysis, we are particularly interested in the complexes that are consistently scored well versus those that consistently scored poorly. GOOD complexes score within 1.1 pKd of the experimental binding affinity for at least 12 of the 17 scoring functions described below, and BAD must be outliers for 12 or more of the scoring functions, see Figure 1. T"). Zilian & Sotriffer chose data involving three targets only. Zilian & Sotriffer, *supra* note 226, at 1924.

227. See *supra* note 182 (illustrating regression).

228. A random decision forest is an AI model that operates by constructing multiple decision trees. Tin Kam Ho, *Random Decision Forests*, in PROCEEDINGS OF 3RD INTERNATIONAL CONFERENCE ON DOCUMENT ANALYSIS AND RECOGNITION 278 (1995).

229. See *supra* notes 195–97 and accompanying text (introducing Pearson's coefficient).

230. Zilian & Sotriffer, *supra* note 226, at 1925.

231. Yang Li & Jianyi Yang, *Structural and Sequence Similarity Makes a Significant Impact on Machine-Learning-Based Scoring Functions for Protein-Ligand Interactions*, 57 J. CHEM. INFO. & MODELING 1007, 1007 (2017).

232. The pregnane X receptor (PXR), "also known as the steroid and xenobiotic sensing nuclear receptor (SXR), is a promiscuous protein encoded by the NR112 (nuclear receptor subfamily 1, group I, member 2) gene." Huali Shi et al., *Absorption, Distribution, Metabolism, Excretion, and Toxicity Evaluation in Drug Discovery. 14. Prediction of Human Pregnane X Receptor Activators by Using Naive Bayesian Classification Technique*, 28 CHEM. RSCH. TOXICOLOGY 116, 116 (2015).

233. *Id.*

will activate PXR is important in the virtual screening stage. Shi et al. trained a Naive Bayesian classification AI model<sup>234</sup> using 532 chemical compounds with known PXR activation activities and achieved an AUC<sup>235</sup> of 0.882.<sup>236</sup> From the prediction results, they also identified twenty important structural fragments as favorable or unfavorable for PXR activation, demonstrating that this AI not only makes great predictions, but also facilitates people's understanding of drug properties.<sup>237</sup>

## 2. Discovery and Design of New Drugs

### a. *De novo* drug design

*De novo* drug design is “the design of novel chemical entities that fit a set of constraints . . . .”<sup>238</sup> The phrase “*de novo*” indicates that one can generate undiscovered or non-existing chemicals “without a starting template.”<sup>239</sup> The benefits of *de novo* drug design include “the exploration of a broader chemical space, design of compounds that constitute novel intellectual property, the potential for novel and improved therapies, and the development of drug candidates in a cost- and time-efficient manner.”<sup>240</sup> A good *de novo* drug design AI should produce drug candidates that not only possess expected biological activities, but also are “chemically diverse” and “contain similar (physico) chemical properties to already known ligands.”<sup>241</sup>

*New drugs against COVID-19.* In response to the urgent need to control the virus that causes COVID-19, the scientific community has been actively looking for drugs against it.<sup>242</sup> For

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234. Naive Bayes is an AI model that assumes the features of an input are uncorrelated with each other. See generally David D. Lewis, *Naive (Bayes) at Forty: The Independence Assumption in Information Retrieval*, in MACHINE LEARNING: ECML-98, at 4 (1998).

235. See *supra* notes 186–90 and accompanying text (introducing AUC).

236. Shi et al., *supra* note 232, at 123–24.

237. *Id.* at 124.

238. Varnavas D. Mouchlis et al., *Advances in De Novo Drug Design: From Conventional to Machine Learning Methods*, 22 INT'L J. MOLECULAR SCI. 1676, 1677 (2021) (citation omitted).

239. *Id.* (citation omitted).

240. *Id.*

241. Xuhan Liu et al., *An Exploration Strategy Improves the Diversity of De Novo Ligands Using Deep Reinforcement Learning: A Case for the Adenosine A<sub>2A</sub> Receptor*, 11 J. CHEMINFORMATICS, no. 35, 2019, at 2.

242. See Samuel Lalmuanawma et al., *Applications of Machine Learning and Artificial Intelligence for Covid-19 (SARS-CoV-2) Pandemic: A Review*, 139

instance, Chenthamarakshan et al. developed a generative modeling framework<sup>243</sup> based on a deep learning approach,<sup>244</sup> CogMol.<sup>245</sup> CogMol has been shown to produce compounds that bind to at least one of three COVID-19-related target proteins of the SARS-CoV-2 virus.<sup>246</sup> When a drug binds a target protein, the protein can no longer bind a cell in a human body and the virus is thereby deactivated to some extent.<sup>247</sup> Impressively, among more than one-thousand compounds produced by CogMol, 87% showed binding capabilities to at least one of the three target proteins,<sup>248</sup> and only thirty-nine are existing compounds.<sup>249</sup> Notably, some of the predicted existing compounds are FDA-approved drugs for other purposes,<sup>250</sup> which relates to drug repurposing, discussed below.

#### b. Drug Repurposing

Drug repurposing, or drug repositioning, refers to the practice of finding new uses for approved drugs.<sup>251</sup> It is “highly attractive because of its potential to speed up the process of drug development, hence reducing costs in addition to providing new treatments for unmet medical needs.”<sup>252</sup>

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CHAOS, SOLITONS & FRACTALS, Oct. 2020, at 1 (reviewing how AI and machine learning were used to solve COVID-19-related problems).

243. “Generative classifiers learn a model of the joint probability,  $p(x, y)$ , of the inputs  $x$  and the label  $y$ , and make their predictions by using Bayes rules to calculate  $p(y|x)$ , and then picking the most likely label  $y$ .” Andrew Ng & Michael Jordan, *On Discriminative vs. Generative Classifiers: A Comparison of Logistic Regression and Naive Bayes*, in 14 ADVANCES IN NEURAL INFORMATION PROCESSING SYSTEMS § 1 (2001). Using the Minnesota weather example, *supra* note 182, a discriminative classifier might predict that the weather in Minnesota tomorrow is cold, but a generative would predict that the probability of cold weather tomorrow is 90%.

244. *See generally* Yann LeCun et al., *Deep Learning*, 521 NATURE 436 (2015).

245. Vijil Chenthamarakshan et al., *CogMol: Target-Specific and Selective Drug Design for COVID-19 Using Deep Generative Models*, in 33 ADVANCES IN NEURAL INFORMATION PROCESSING SYSTEMS 1 (2020).

246. *Id.* at 3.

247. *See supra* note 225 for introduction of antagonists.

248. *Id.* at 6–7.

249. *Id.* at 6 (“Only 19, 5, and 15 of the generated molecules match exactly with an existing [compounds] . . .”).

250. *Id.* at 3.

251. Francesco Napolitano et al., *Drug Repositioning: A Machine-Learning Approach Through Data Integration*, 5 J. CHEMINFORMATICS, 2013, at 1, 2.

252. *Id.* at 1.

*New anti-cancer drugs.* Napolitano et al. developed a novel approach to find alternative uses for existing drugs.<sup>253</sup> Specifically, the group trained an AI classifier to predict therapeutic effects using thousands of FDA-approved drugs,<sup>254</sup> and then applied it to 410 drugs, obtaining a classification accuracy of 78%.<sup>255</sup> The group claimed this accuracy is adequately reliable to assist drug repurposing.<sup>256</sup> In other words, instead of treating mismatches between known and predicted drug classifications as pure errors, the model was allegedly reliable enough to allow people to interpret the mismatches as hints for other therapeutic effects of the drugs.<sup>257</sup> In conclusion, with the assistance of AI, the group reported several existing non-cancer-related drugs to have anticancer potential with trackable mechanisms.<sup>258</sup>

### 3. Guiding Synthesis Process

In addition to knowing the composition and properties of promising drug candidates, it is also important to know how to synthesize them. An AI's capability to predict chemical reactions and design retrosynthesis routes allows people to rationally synthesize new molecules.<sup>259</sup> Reactions prediction proceeds in a forward direction as "the task is to infer how a set of molecules (starting materials) will react and what the product will be."<sup>260</sup> By contrast, retrosynthesis goes in a reverse direction, wherein "the aim is to propose how to make a target molecule, by deducing reactions where the target molecule is the product."<sup>261</sup>

#### a. Reaction Prediction

*New reactions from failures.* To train an AI to predict whether a given reaction will happen, training data must

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253. *Id.* at 2.

254. Specifically, Napolitano et al. used gene expressions of 1265 drugs, chemical structures of 6594 drugs, and biological targets of 1571 drugs to train the model. The three databases had 410 drugs in common, which were later fed into the classifier for repurposing. *Id.* at 2, 6.

255. *Id.* at 2–3.

256. *Id.*

257. *Id.*

258. *Id.* at 5.

259. *See infra* Sections II.B.3.a–b.

260. Segler & Waller, *supra* note 152, at 5966.

261. *Id.*

include both successful and failed reactions.<sup>262</sup> While successful reactions can be obtained from published literature, “the failed vast majority of unreported . . . reactions are archived in laboratory notebooks that are generally inaccessible.”<sup>263</sup> Realizing this problem, Raccuglia et al. trained an AI based on the SVM model<sup>264</sup> to predict whether a set of reactions will yield inorganic-organic crystal products using not only the successful experiment records, but also failed experiment records from their own lab notebooks.<sup>265</sup> Surprisingly, the reaction predictions achieved an accuracy of 89%, higher than the human expert’s intuition accuracy rate of 78%.<sup>266</sup> Interestingly, to overcome the poor interpretability of SVM models<sup>267</sup> the group used the training data and corresponding predictions to train a decision tree,<sup>268</sup> which is much easier to interpret.<sup>269</sup> This innovative step allowed them to make plausible hypotheses about the conditions that contribute to the success of reactions and revealed “previously unknown insights into . . . chemistry.”<sup>270</sup>

#### b. Retrosynthesis

*Sophisticated route design.* AI for retrosynthesis has been criticized for containing easily recognizable “chemically unreasonable steps.”<sup>271</sup> Segler et al. attempted to solve this problem with a two-part AI.<sup>272</sup> First, the group trained an AI

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262. See generally *supra* Section II.A.1 (introducing requirements for data in AI developing processes).

263. Paul Raccuglia et al., *Machine-Learning-Assisted Materials Discovery Using Failed Experiments*, 533 NATURE 73, 73 (2016).

264. A support vector machine (SVM) is an AI model that operates by finding a hyperplane which best separates input data. See generally M. A. Hearst et al., *Support Vector Machines*, 13 IEEE INTEL. SYS. & THEIR APPL. 18 (1998).

265. Raccuglia et al., *supra* note 263, at 73.

266. *Id.* at 74.

267. See *supra* note 175.

268. A decision tree is a tree-like AI model, where each node of the tree represents a test for making a decision, and edges below a node, if any, lead to different consequences according to the test results. See generally J. R. Quinlan, *Induction of Decision Trees*, 1 MACH. LEARNING 81 (1986).

269. Raccuglia et al., *supra* note 263, at 74.

270. *Id.* at 76.

271. Marwin H. S. Segler et al., *Planning Chemical Syntheses With Deep Neural Networks And Symbolic AI*, 555 NATURE 604, 607 (2018).

272. *Id.* at 605.

based on the Monte Carlo tree search (MCTS)<sup>273</sup> using millions of reactions.<sup>274</sup> The first AI is able to produce synthesis routes for a given molecule with a “top 50 accuracy”<sup>275</sup> of 72.5%.<sup>276</sup> The group then trained a second AI based on a deep neural network<sup>277</sup> to predict whether the reactions of a synthesis route recommended by the first AI would be feasible.<sup>278</sup> The final AI integrates the first and second AIs to form the so-called “3N-MCTS AI,” in which the routes recommended by the MCTS part (the first AI) are filtered by the 3N part (the second AI, using a total of three neural networks, hence “3N”).<sup>279</sup> The AI’s overall performance reached a 92% problem solve rate within sixty seconds, showing an incredible capacity for fast designing synthesis routes.<sup>280</sup> Circling back to the aforementioned challenge, the group also performed a double-blind survey;<sup>281</sup> the result showed that experts did not prefer literature routes over routes designed by the AI with any statistical significance.<sup>282</sup>

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273. Monte Carlo tree search is a tree-like AI model that looks for most promising next steps based on random sampling of the search space. *See generally* Cameron B. Browne et al., *A Survey of Monte Carlo Tree Search Methods*, 4 IEEE TRANSACTIONS ON COMPUTATIONAL INTEL. & AI GAMES 1 (2012).

274. Segler et al., *supra* note 271, at 604.

275. The “top 50 accuracy” is the percentage of results where the correct route is among the top fifty recommended routes by the AI. *See, e.g.*, Rushabh Nagda, *Evaluating Models Using the Top N Accuracy Metrics*, NANONETS (Nov. 8, 2019), <https://medium.com/nanonets/evaluating-models-using-the-top-n-accuracy-metrics-c0355b36f91b>.

276. Segler et al., *supra* note 271, at 605.

277. Deep neural network is an AI model that mimics the neural networks in a human brain. *See generally* Yang et al., *supra* note 154, at 10531–32.

278. Similar to the challenge stated in Raccuglia et al., *supra* note 263, Segler et al. also needed failed reactions as negative data to train the AI to predict reaction feasibility. Segler et al., *supra* note 271, at 605. To solve this problem, Segler et al. used “implicit information about reactions that do not occur” from published reactions. *Id.* For example, for “a high-yielding reaction  $A + B \rightarrow C$ , [it can be assumed] that hypothetical products D, E, . . . are not formed.” *Id.* Using this logic, the group obtained negative reactions by “shuffling the associated pairs of products and corresponding reactions.” *Id.*

279. *Id.* at 605–06.

280. *Id.* at 607.

281. “Double-blind” means “neither the participants nor the conductors were aware of the origin of the routes.” *Id.* Specifically, participants here were forty-five graduate-level organic chemists from two world-leading organic chemistry institutes in China and Germany. *Id.*

282. *Id.* Informally, this statement can be understood as it is possible that the experts did not prefer literature routes statistically. *See generally* JEROME

This work is impressive because it “can be initially set up within a few days without the need for tedious and biased expert encoding or curation[,] applicable to discipline-scale datasets,” and the synthesis routes can be proposed in seconds and are non-inferior to the ones designed by human experts.<sup>283</sup>

### C. ACCESSIBILITY AND LIMITATION OF AI

While AI is making an irreplaceable contribution to R&D in traditionally unpredictable arts, its impact on the general public depends on whether the AI sources are accessible and whether the resources are useful.

#### 1. Accessibility

The accessibility of AI as a tool to the public relies on three factors: open data, open software, and open education.<sup>284</sup>

##### a. Database

Data is one of the fundamental elements that allows researchers to perform novel research and repurpose published works.<sup>285</sup> The scientific community has been striving to make more data publicly accessible.<sup>286</sup> Nowadays, there are more than fifty material-related databases<sup>287</sup> and more than forty drug-related databases,<sup>288</sup> including millions of data entries for

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L. MYERS ET AL., RESEARCH DESIGN AND STATISTICAL ANALYSIS 65–90 (3d ed. 2010).

283. Segler et al., *supra* note 271, at 609.

284. Butler et al., *supra* note 152, at 548.

285. *See supra* text accompanying notes 157–58.

286. Joanne Hill et al., *Materials Science with Large-Scale Data and Informatics: Unlocking New Opportunities*, 41 MRS BULL. 399, 404 (2016) (“The open-access (OA) paradigm, in which readers are able to view and (sometimes) repurpose published research at no cost, is gaining traction as key stakeholders jump on board. More publishers are adopting OA models, and increasing numbers of papers are appearing under a creative commons license, which makes content and data freely available. The Nature Publishing Group, for example, launched the journal *Scientific Data* in 2014, which is OA and dedicated specifically to redistributing important scientific data sets.”).

287. *See id.* at 402–03 tbl. I (listing notable materials data resources); Butler et al., *supra* note 152, at 552 tbl. 3 (listing publicly accessible databases for molecules and solids).

288. *See* Ruolan Chen et al., *Machine Learning for Drug-Target Interaction Prediction*, 23 MOLECULES, no. 9, 2018, at 5–6, tbls. 1–2 (listing databases supporting drug discovery methods and the statistics thereof); Wen Zhang et al., *Recent Advances in the Machine Learning-based Drug-target Interaction Prediction*, 20 CURRENT DRUG METABOLISM 194, at 194–97 (2019) (listing

general and specific purposes, and the total data amount keeps increasing.<sup>289</sup> In addition to the organized databases, it is also possible for researchers to extract data from publications.<sup>290</sup>

#### b. Software and Education

There are a few freely available ML-based software programs ready for use towards specific problems,<sup>291</sup> such as AFLOW-ML for predicting electronic, thermal and mechanical properties of materials,<sup>292</sup> AdmetSAR 2 for predicting absorption, distribution, metabolism, excretion, and toxicity of drug candidates,<sup>293</sup> and AlphaFold for predicting 3D structures of proteins.<sup>294</sup> Many of these software programs can be used by a simple “drag-and-drop” method, or by typing the descriptors of compounds of interest.<sup>295</sup>

Motivated by the strong power of AI and its increasing market, some corporations have formed to develop AI tools according to clients’ needs.<sup>296</sup> Other businesses have emerged to

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databases for drug discovery); Andy H. Vo et al., *An Overview of Machine Learning and Big Data for Drug Toxicity Evaluation*, 33 CHEM. RSCH. TOXICOLOGY 20, 26 tbl. 3 (2019) (listing toxicity databases for drug safety evaluation).

289. See Hill et al., *supra* note 286, at 406 (“The amount of data in the materials community, as in many other areas of science and human endeavor, is increasing exponentially . . .”); Chen et al., *supra* note 288, at 4 (“Some of these databases are being updated frequently, such as DrugBank, KEGG, and STITCH . . .”).

290. See, e.g., *supra* text accompanying notes 262–70, 278.

291. Dane Morgan & Ryan Jacobs, *Opportunities and Challenges for Machine Learning in Materials Science*, 50 ANN. REV. MATERIALS RSCH. 71 supp. at 5–6 (2020) (listing machine learning software for material engineering); Vo et al., *supra* note 288, at 24 tbl. 1 (listing machine learning tools for extraction of molecular descriptors and fingerprints).

292. See generally Eric Gossett et al., *AFLOW-ML: A RESTful API for Machine-Learning Predictions of Materials Properties*, 152 COMPUT. MATERIALS SCI. 134 (2018).

293. See generally Hongbin Yang et al., *admetSAR 2.0: Web-Service for Prediction and Optimization of Chemical ADMET Properties*, 35 BIOINFORMATICS 1067 (2019).

294. See, e.g., John Jumper et al., *Highly Accurate Protein Structure Prediction with AlphaFold*, 596 NATURE 583 (2021) (stating that AlphaFold is a network-based model that can predict “the 3d structure that a protein will adopt based solely on its amino acid sequence”).

295. See, e.g., *id.*

296. See, e.g., *AI software development for Chemistry and Materials R&D*, CHEMINTELLIGENCE, <https://chemintelligence.com/ai-software-development> (last visited Feb. 18, 2022) (advertising for “tailored AI software that accelerates [clients] R&D”).

provide assistance or cooperation using AI to aid in the research process of their clients.<sup>297</sup>

Furthermore, thousands of papers presenting the applications of AI to various scientific disciplines are published every year.<sup>298</sup> Many authors have made their accompanying source codes open to the public along with their publications.<sup>299</sup> Accordingly, researchers can follow published AI methods and adapt published codes, if available, in order to develop their own AI.

Finally, there are plenty of educational resources available for researchers with no AI background to learn how to develop AI by themselves.<sup>300</sup> One can use a variety of programs to develop AI,<sup>301</sup> and numerous available machine learning packages in different languages are making this even easier.<sup>302</sup>

## 2. Inaccessibility and Limitation

The availability of large quantities of data is what made AI possible.<sup>303</sup> Conversely, limiting access to data would limit the application of AI. At present, available data is still less than adequate for training AI in many scenarios, especially for drug discovery purposes.<sup>304</sup> Moreover, not all databases are freely

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297. See Moe Elbadawi et al., *Advanced Machine-Learning Techniques in Drug Discovery*, 26 DRUG DISCOVERY TODAY 769, 770 tbl. 1 (2021) (showing “examples of pharmaceutical companies in which ML is central to their business model”).

298. See Zachary J. Baum et al., *Artificial Intelligence in Chemistry: Current Trends and Future Directions*, 61 J. CHEM. INFO. & MODELING 3197, 3198 fig. 1 (2021) (showing the number of chemistry publications using AI from 2000 to 2020); Morgan & Jacobs, *supra* note 204, at 73 fig. 1 (showing the number of ML-related publications in material science and engineering from 2003 to 2019); Zhang et al., *supra* note 288, at 195 fig. 1 (showing the number of publications related to machine learning and drug-target interactions from 2007 to 2017).

299. Mouchlis et al., *supra* note 238, at 1690 (arguing that “[s]haring of tools and approaches, via an open innovation model, is [an] essential approach” to facilitating the use of AI in research).

300. Butler et al., *supra* note 152, at 550 (listing education resources for machine learning).

301. Lavecchia, *supra* note 175, at 328 tbl. 1 (listing programs that implement machine learning processes).

302. Butler et al., *supra* note 152, at 550 tbl. 2 (listing publicly accessible machine learning packages).

303. See *supra* Section II.B.

304. See, e.g., Mouchlis et al., *supra* note 238, at 1690–91 (“[I]t is well-known that only a small fraction of the chemical space has been sampled in the search

available.<sup>305</sup> Some useful data are never revealed to the public and are instead carefully guarded as trade secrets.<sup>306</sup> To make things worse, data in different disciplines are diversified in format and available features.<sup>307</sup> Data obtained under different conditions can differ significantly.<sup>308</sup> A considerable portion of existing data is not well annotated or is inaccessible.<sup>309</sup> All of this adds difficulty to research based on big data.

The expertise and skill required by the AI development process also contributes to its inaccessibility.<sup>310</sup> For example, in addition to the original information about chemicals, the representation of chemicals impacts the performance of AI as well.<sup>311</sup> Counterintuitively, a more precise representation of chemicals does not necessarily lead to better AI performance, as higher precision may introduce more noise and make the data pattern more complex for AI to recognize.<sup>312</sup> Accordingly, finding a representation that gives the best AI performance can be tricky.

Lastly, although AI can be used to make predictions with a high degree of accuracy, the potential factors underlying those predictions cannot always be easily understood.<sup>313</sup> To

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for novel drug candidates.”); Wu et al., *supra* note 209, at 16 (“[T]he number of cancer cell lines and drugs is limited, which may affect the model generalizability in predicting novel drug combinations.”).

305. Hill et al., *supra* note 286, at 402–03 tbl. I (listing notable materials data resources including free and non-free databases).

306. *Id.* at 405 (“Proprietary data exist in abundance, but many producers of materials carefully guard their manufacturing data as trade secrets . . .”).

307. *See id.* at 401 (“The current materials data landscape is a highly fragmented patchwork quilt of smaller databases, each customized to present information from a specific subdiscipline.”).

308. *E.g.*, Vo et al., *supra* note 288, at 30 (“However, data integrated from in vitro bioassays and in vivo studies can differ significantly between multiple sources. Experimental design differences such as dosage, animal models used, technologies used, or length of study can often give different or even conflicting outcomes.” (citation omitted)).

309. *Id.*

310. *See, e.g.*, *supra* Sections II.A.1–2.

311. *See supra* notes 163–67 and accompanying text.

312. Pedro J. Ballester et al., *Does a More Precise Chemical Description of Protein-Ligand Complexes Lead to More Accurate Prediction of Binding Affinity?*, 54 J. CHEM. INFO. MODELING 944, 945. (“[A] more precise chemical description of the protein–ligand complex does not generally lead to a more accurate prediction of binding affinity.”); *id.* at 952 (“[M]ore precise descriptors often mean making modeling assumptions that introduce additional error.”).

313. *E.g.*, Wu et al., *supra* note 209, at 16–17 (“Especially through [deep learning] models, although they can get relatively accurate prediction results,

understand the physical, chemical, and/or biological mechanisms behind AI prediction results, further research might be needed.

### III. USING AI PREDICTIONS IN PATENT PRACTICE

#### A. AI'S POTENTIAL OF FACILITATING PATENT PRACTICE UNDER THE CURRENT LEGAL FRAMEWORK

Just as AI is helping significantly reduce the R&D cycle of traditional unpredictable arts,<sup>314</sup> it should also help reduce the patent application cycle in these arts. This Section discusses how patent practitioners can properly use AI predictions to enable them to file applications early and safely.

##### 1. A Recommended Practice

###### a. Rationally Tailor Claim Scope

Under current case law, by providing more guidance, a patentee can always make his or her patent viewed more favorably with respect to all *Wands* factors except the factor of experimentation amount.<sup>315</sup> That is, if experimentation is still necessary for practicing a claim,<sup>316</sup> the claim is not enabled if the

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the potential factors affecting the prediction results cannot be understood.”); Chen et al., *supra* note 288, at 11 (“[M]ost machine learning models possess ‘poor interpretability’ properties. In other words, it is difficult to understand the underlying drug mechanism of action from a biological perspective.”).

314. See *supra* text accompanying note 208; see also Hill et al., *supra* note 286, at 399 (“[T]he potential impact of data-driven materials science is tremendous: Materials informatics could reduce the typical 10–20 year development and commercialization cycle 5 for new materials.”).

315. See *supra* Section I.A.1.

316. This is almost always true for AI-assisted patent applications in technical fields where the art is traditionally unpredictable. Theoretically, an AI can be 100% accurate, but only if it is designed for “a quite simple and stationary problem.” Jose-Marcio, *Why Can't Machine Learning/Deep Learning Algorithms Be a 100% Accurate at Test Time?*, QUORA (June 23, 2019), <https://www.quora.com/Why-cant-machine-learning-deep-learning-algorithms-be-a-100-accurate-at-test-time>. Uncertainties in AI come from various sources, including randomness in data collection, order of data observation, the algorithm, sampling, and resampling. See Jason Brownlee, *Embrace Randomness in Machine Learning*, MACH. LEARNING MASTERY (Aug. 12, 2019), <https://machinelearningmastery.com/randomness-in-machine-learning/>.

Accordingly, AI for solving problems with a real-world value can hardly achieve a 100% accuracy. Moreover, it is unclear how much predictability can release a patentee from performing experiments. See discussion *infra* Section III.B (discussing limitations of the existing legal framework).

experimentation for practicing the claim exceeds a reasonable amount, even if the experimentation is routine.<sup>317</sup> Nevertheless, one can only reduce the amount of experimentation by tailoring the claim scope.<sup>318</sup>

Limiting the amount of experimentation is especially pertinent where a claim includes functional limitations<sup>319</sup> and species that possess the claimed structural features far outnumber those that also satisfy the functional limitations.<sup>320</sup> In such scenarios, a PHOSITA may need to perform a huge amount of experimentation to find the species that possess both functional and structural limitations out of those possessing structural limitations only.<sup>321</sup>

To reduce the amount of (routine) experimentation, this Note recommends using AI predictions to rationally tailor claims similar to the hypothetical claim above,<sup>322</sup> which (1) specifies more detailed functions and/or properties and (2) removes species that are predicted to be unlikely to possess such functions and/or properties. For example, instead of claiming compounds for treating disease X, an applicant is better off claiming compounds that have high binding affinities<sup>323</sup> to biomolecular targets identified as related to disease X.

Using such a claiming approach has several advantages. First, it fits the prediction capability of current AI.<sup>324</sup> Inventing a new drug for treating a disease is very complex.<sup>325</sup> Few, if any,

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317. See *supra* Section I.A.1.d.

318. *Id.*

319. See *supra* note 129 (introducing functional limitations).

320. See, e.g., *Idenix Pharms. LLC v. Gilead Scis. Inc.*, 941 F.3d 1149, 1162 (Fed. Cir. 2019) (holding the patent at issue was not enabled because “a reasonable jury could only have found that at least many, many thousands of [species] meet the structural limitations of claim 1, not all of which [meet the functional limitation]”).

321. *Id.* (“[T]he ‘597 patent leaves a POSA searching for a needle in a haystack to determine which of the ‘large number’ of 2'-methyl-up nucleosides falls into the ‘small’ group of candidates that effectively treats HCV.”).

322. The hypothetical claim is reproduced here for convenience: A drug for a disease X, consisting of a main structure M and an element attached to the main structure M, wherein the element is A, B, or C. Arguments regarding this hypothetical claim are applicable to any claim comprising structural and functional limitations.

323. See *supra* notes 223, 225 (introducing binding affinity).

324. See *supra* Part II.C.1 (showing examples in which AI predict binding affinities for certain molecules with satisfactory accuracy).

325. The extensive R&D cycles of a drug are a testament to the complexities of drug development. See Jack W. Scannell et al., *Diagnosing the Decline in*

AI have been developed for predicting whether a drug candidate is effective for mitigating a given disease. Instead, AI are usually developed for more specific purposes, such as predicting drug binding affinities to a specific target, or the toxicity, absorption, and metabolism of a drug.<sup>326</sup> Second, it strengthens the claim against potential indefiniteness rejections.<sup>327</sup> The standard for a drug to be effective against a certain disease is not necessarily established in the art, but an applicant may need to define what “effective” means in his or her application.<sup>328</sup> By contrast, claiming compounds with a binding affinity higher than a specified level is clear by itself, and a PHOSITA will be better noticed of the metes and bounds of the claim.<sup>329</sup> Third, it satisfies

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*Pharmaceutical R&D Efficiency*, 11 NATURE REVS. DRUG DISCOVERY 191 (2012) (showing that drug developing processes are lengthy and costly). But in the context of patent law, a drug may be regarded as useful for treating a disease even if no human clinical trials have been performed. *See supra* note 111 and accompanying text. Nevertheless, there may be more than one tractable mechanism for treating a disease. *See, e.g., supra* text accompanying notes 242–47. Therefore, it is much harder for a PHOSITA to experiment for whether a compound is effective for a disease than for whether the compound has some effects on a certain biomolecular target. *See Idenix Pharms. LLC v. Gilead Scis. Inc.*, 941 F.3d 1149, 1158 (Fed. Cir. 2019) (“Testing the compounds in the specification alone for efficacy against HCV requires enough experimentation for this factor to weigh in favor of non-enablement. Idenix relatedly argues that a POSA would understand the ‘focus’ of the claim to be ‘the inhibition of the NS5B polymerase’ to effectively cure HCV. Therefore, Idenix argues, a POSA would know which candidates were likely to inhibit NS5B, and would test only those, resulting in a ‘predictable and manageable’ group of candidate compounds.” (citation omitted)).

326. *See supra* Section II.C.1 (presenting examples in which AI were developed to predict specific properties of drug candidates).

327. 35 U.S.C. § 112(b) (1952) (“The specification shall conclude with one or more claims *particularly pointing out and distinctly claiming the subject matter* which the inventor or a joint inventor regards as the invention.” (emphasis added)).

328. “[C]laim terms are typically given their ordinary and accustomed meaning as understood by one of ordinary skill in the pertinent art.” *Medrad, Inc. v. MRI Devices Corp.*, 401 F.3d 1313, 1318 (Fed. Cir. 2005). But if there is no established ordinary meaning for a term recited in a claim, the applicant would have to clearly define it in the patent specification to avoid violating the definiteness requirement. *See, e.g., Icon Health & Fitness, Inc. v. Polar Electro Oy*, 656 F.App’x 1008, 1014–15 (Fed. Cir. 2016) (affirming indefiniteness of claims reciting “in-band” and “out-of-band” communications because there were no established meanings of “in-band” and “out-of-band” communications and the patentee failed to define the terms either).

329. *See McClain v. Ortmayer*, 141 U.S. 419, 424 (1891) (“The object of [the definiteness requirement] is not only to secure to him all to which he is entitled, but to apprise the public of what is still open to them.”).

the utility requirement. As stated above, an *in vitro* efficacy that bears a correlation with *in vivo* efficacy satisfies the utility requirement for a drug that is claimed to be effective for a certain disease.<sup>330</sup> Accordingly, the binding affinities provided by AI predictions, which are more likely to be measured *in vitro*, are sufficient to support the utility of the claimed compounds.<sup>331</sup> Lastly, since the species predicted to be ineffective are removed from the claim scope by the AI, the total species covered by the claim will be much fewer.<sup>332</sup> Fewer species mean less unnecessary experimentation, which in turn helps the claim pass the enablement requirement.<sup>333</sup>

#### b. Provide a Representative Number of Species

When AI learns a model from training data, it is learning the pattern of the data.<sup>334</sup> AI makes predictions based on the learned pattern.<sup>335</sup> Hence, molecules that are predicted to show similar properties must possess similar features because all predictions follow the same pattern. This means the predicted results can necessarily be represented by a small portion of them.<sup>336</sup> Suppose that the claim scope has been rationally

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330. See *supra* text accompanying note 111.

331. A drug's binding affinity to a given target and the drug's efficacy against a disease related to the target are always closely correlated for antagonists, but not for agonists. See *supra* note 225. If the drug to be patented is an agonist, one should consider providing the drug's efficacy to the target in addition to the binding affinity so as to demonstrate that there is a satisfactory correlation between the *in vitro* data and prospective effects in human bodies. *Id.*

332. For example, if the patentee in *Idenix Pharms. LLC v. Gilead Scis. Inc.* rationally tailored its claim as recommended, the claim would cover much fewer species. 941 F.3d 1149, 1162 (Fed. Cir. 2019) (“[T]he [patent-at-issue] leaves a POSA searching for a needle in a haystack to determine which of the ‘large number’ of 2'-methyl-up nucleosides falls into the ‘small’ group of candidates that effectively treats HCV.” (citations omitted)).

333. See *supra* Section I.A.1.d (demonstrating that under current case law, the enablement requirement implicates the necessary experimentation for practicing a claim cannot exceed a reasonable amount).

334. See *supra* Section II.A.2 (introducing the process of training AI).

335. See *id.* (introducing how AI makes predictions).

336. In many cases, one can find the pattern of predicted results by observation. See, e.g., Stanev et al., *supra* note 183, at 9 tbl. 3 (listing compounds predicted to have superconductivity potentials, where, for example, KSbO<sub>2</sub>, RbSbO<sub>2</sub>, and CsSbO<sub>2</sub> are different in only one element, and the different elements belong to the same chemical group). Concededly, there are cases where the AI predictions are difficult to interpret. See *supra* text accompanying note 313. In such cases, one may consider extra strategies to extract common

tailored according to AI predictions, as recommended above. One may reasonably expect that species within the small portion will possess enough similarity with some species in the remaining portion and be diverse enough to cover substantial differences among all species of the claimed genus, thus constituting a representative number of species.<sup>337</sup>

One should then experimentally confirm whether the representative species possess desired properties and/or functions. Given that the scope of the genus claim has already been rationally narrowed, experimentation on these representative species should not cost significant time or money.<sup>338</sup> Alternatively, an applicant may as well refer to experiment data of these species provided in publications, if available. Supporting the representative species with experimentally confirmed data is a safeguard against written description challenges, according to current case law.<sup>339</sup>

As a final note to this recommended practice: if the claim covers species which are not available off the shelf, then the patent disclosure should include guidance on how to make such species.<sup>340</sup> The applicant may refer to available synthesis routes listed in other publications, if any. If the claim covers *de novo* compounds for which no experimentally confirmed synthesis routes are available, the applicant may consider developing or using an available AI to predict synthesis routes, and confirming, theoretically and/or experimentally, that the predicted routes are feasible.<sup>341</sup>

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features of the predicted results. *See, e.g.*, Stanev et al., *supra* note 183, at 10; Shi et al., *supra* note 232, at 120–21; Raccuglia et al., *supra* note 263, at 74.

337. *See supra* Section I.B.1 (describing the claiming tactic of a “representative number of species”).

338. In addition to the fact that only a few species are covered by a rationally tailored claim, the specific function/property recited in the claim can be experimentally confirmed more easily than a general function of treating a disease. *See supra* note 325.

339. *See, e.g.*, *Invitrogen Corp. v. Clontech Lab’ys, Inc.*, 429 F.3d 1052 (Fed. Cir. 2005); *Ex Parte Gleave*, 2006 WL 6927761 (B.P.A.I. 2006).

340. *See* 35 U.S.C. § 112(a) (“The specification shall contain a written description of the invention, and of the manner and process of *making* and using it . . . .” (emphasis added)).

341. *See supra* Section II.B.3 for information about AI application in design chemical synthesis routes.

## 2. Alternative Options

### a. Claim by Structure

It is also possible to use AI predictions to claim by structure, without adding functional limitations. Nevertheless, this is not necessarily a better way of claiming. Certainly, claiming by structure is less susceptible to indefiniteness rejections, and seems to be more easily enabled due to the lack of functional limitation.<sup>342</sup> But the claim still has to satisfy the utility requirement.<sup>343</sup> Accordingly, if many species possessing the recited structure do not show the identified utility, the claim will still be found invalid for failing the utility requirement (and thus the enablement requirement), unless a PHOSITA is able to distinguish the operative species without undue experimentation—harkening back to the original enablement issue.<sup>344</sup>

### b. Incorporate AI Development as Part of the Guidance

Instead of claiming the end results of AI predictions, some applicants might prefer to claim broadly and include AI development as part of the guidance for enablement purposes. It is outside the scope of this Note to assert which claiming approach makes more business sense. Nevertheless, the approach of claiming broadly and disclosing AI development techniques makes less legal sense.

Courts would likely be more averse to this approach than the recommended one because such claims are more likely to overreach.<sup>345</sup> Courts might be unable to invalidate such claims under the enablement requirement if it can be shown that a PHOSITA is able to follow the guidance to develop an AI with good performance and if necessary experimentation is not undue in view of AI predictions.<sup>346</sup> Yet courts could still strike down the claims based on the written description requirement.<sup>347</sup> AI is likely, if not always, to provide predictions with some

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342. See *supra* text accompanying notes 319–21.

343. See *supra* Section I.A.2.

344. *Id.*

345. See *supra* text accompanying notes 117–18.

346. See *supra* Section I.A.1 (discussing the *Wands* factors for constituting undue experimentation).

347. See *supra* note 125.

randomness.<sup>348</sup> Hence, there is hardly any guarantee that the list an applicant provides based on his or her own AI will represent the species in the broad claim scope.<sup>349</sup> If the opposing party can produce evidence to this effect, the validity of the claim is at risk.

### 3. A Flip Side: Obviousness?

While increased predictability makes a patent stronger against enablement and written description requirements, it may nevertheless render a patent weaker against obviousness rejections.<sup>350</sup> Non-obviousness is a statutory requirement for patents under 35 U.S.C. § 103:

A patent for a claimed invention may not be obtained . . . if the differences between the claimed invention and the prior art are such that the claimed invention as a whole would have been obvious before the effective filing date of the claimed invention to a person having ordinary skill in the art to which the claimed invention pertains.<sup>351</sup>

For a claimed invention to be obvious, the invention must be such that a PHOSITA can reasonably expect that the invention will be successful, or in the languages of patent law, be operable in view of the prior art.<sup>352</sup> A reasonable expectation of success in turn requires some predictability of the art. Consequently, the predictability of an invention works against non-obviousness.<sup>353</sup>

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348. See *supra* note 321.

349. If the claim scope has not been tailored according to the AI predictions, then it is possible that the AI predictions missed one or more significant species within the scope of the claim due to the inherent randomness of its predictability model. See *supra* note 316 (discussing the inherent randomness existing in most AI).

350. See generally David Tseng, *Not All Patents Are Created Equal: Bias Against Predictable Arts Patents in the Post-KSR Landscape*, 13 CHI.-KENT J. INTELL. PROP. 165 (2013) (arguing the decision of *KSR Int'l. Co. v. Teleflex Inc.*, 550 U.S. 398 (2007) and subsequent USPTO guidelines, *infra* note 353, made it much easier for predictable art patents to be held obvious, even to an unfair extent).

351. 35 U.S.C. § 103 (1952).

352. *In re Merck & Co.*, 800 F.2d 1091, 1097 (Fed. Cir. 1986) (“[A] reasonable expectation that the beneficial result will be achieved is necessary to show obviousness.”).

353. See Examination Guidelines for Determining Obviousness Under 35 U.S.C. § 103 in View of the Supreme Court Decision in *KSR International Co. v. Teleflex Inc.*, 72 Fed. Reg. 57,526, 57,529 (Oct. 10, 2007) [hereinafter *KSR Guidelines*] (listing seven rationales for finding obviousness, five of which include predictability as a factor).

So will an increase in predictability due to AI development make inventions in the traditionally unpredictable arts more susceptible to an obviousness challenge? It depends.

As discussed above, databases, AI software, and developing tools are not equally accessible.<sup>354</sup> For inventions that can be created by freely available, easy-to-use databases and AI software, there is a strong argument that the level of PHOSITA is improved by the AI resources.<sup>355</sup> For example, traditionally, to determine the 3D structure of a protein, researchers have to first crystallize a protein with a high purity and determine its structure through various experiments.<sup>356</sup> This process is time-consuming and does not necessarily generate an accurate result, as there can be errors made in each of the many steps of the experiments.<sup>357</sup> Now, this process can be performed by the AI tool AlphaFold quickly and reasonably accurately.<sup>358</sup> As a result, any invention in which the only “inventive” part is the knowledge of a protein structure may be rendered obvious, as anyone having ordinary skills in biology and computing could use AlphaFold to obtain the protein structure, unless AlphaFold wrongly predicts a protein structure and a PHOSITA is effectively taught away by the prediction.<sup>359</sup> This is not to say that a free, capable AI tool will necessarily kill a patent. There are plenty of other ways to establish non-obviousness, including

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354. See *supra* Part II.C.2 (discussing inaccessibility concerns with AI).

355. Again, a PHOSITA is a “hypothetical person who is presumed to be aware of all the pertinent prior art.” See *supra* note 75 and accompanying text. Freely available AI resources are in the public domain, which a PHOSITA is presumed to be aware of. *Id.*

356. *Determining Protein Structure*, NEOS GUIDE, <https://neos-guide.org/content/protein-structure> (last visited Jan. 26, 2022) (introducing the process for determining the 3D structure of a protein).

357. See Jumper et al., *supra* note 294, at 583 (“Structural coverage is bottlenecked by the months to years of painstaking effort required to determine a single protein structure.”).

358. *Id.*

359. Teaching away is a common argument against obviousness. See, e.g., *W.L. Gore & Assocs., Inc. v. Garlock, Inc.*, 721 F.2d 1540, 1551 (Fed. Cir. 1983) (holding the claims at issue were not obvious because “the [prior] art as a whole teaches the other way”). “A reference may be said to teach away when a person of ordinary skill, upon reading the reference, would be discouraged from following the path set out in the reference, or would be led in a direction divergent from the path that was taken by the applicant.” *In re Gurley*, 27 F.3d 551, 553 (Fed. Cir. 1994).

spotting a non-obvious problem<sup>360</sup> and making non-obvious use or improvement of the results given by the AI tool.

For problems that cannot be readily addressed by AI resources, innovation and non-obviousness may exist in the development process of AI. Overcoming the limitation of data<sup>361</sup> can be an innovative starting point of a work.<sup>362</sup> The overall AI training method is also non-obvious because the representation of data, choice of models, and process of finding parameters all require expertise and insight into the problem at hand.<sup>363</sup> Moreover, although some AI work by finding promising candidates from a candidate pool specified by its developer, which may constitute choosing from “a finite number of identified, predictable solutions,”<sup>364</sup> the challenging process of narrowing down thousands or even millions of candidates cannot be deemed to be obvious. Finally, AI is not guaranteed to find a solution to a given problem,<sup>365</sup> which provides another argument against applying the “obvious to try” rationale to AI-assisted inventions.<sup>366</sup>

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360. See, e.g., *Omeprazole Patent Litig. v. Apotex Corp.*, 536 F.3d 1361, 1380 (Fed. Cir. 2008) (finding a drug preparation process including coating omeprazole with an inert material non-obvious, in which omeprazole was a known drug, the inert material was known but had not been used for coating, and the coating process was known, because “a person of ordinary skill in the art would not have inferred from the [prior art] that a negative interaction [between omeprazole and the available coating materials] would occur”).

361. See *supra* Part II.C.2 (discussing how data inaccessibility limits AI).

362. See *supra* note 163 and accompanying text (providing examples of developers using innovative strategies to obtain more data).

363. See *supra* Section II.A (introducing a general workflow of AI).

364. See *KSR Int'l. Co. v. Teleflex Inc.*, 550 U.S. 398, 421 (2007) (“When there is a design need or market pressure to solve a problem and there are a *finite number of identified, predictable solutions*, a person of ordinary skill has good reason to pursue the known options within his or her technical grasp. If this leads to the anticipated success, it is likely the product not of innovation but of ordinary skill and common sense.” (emphasis added)).

365. Yang et al., *supra* note 154, at 10538 (“One should keep in mind that . . . the data sets used for machine learning in drug discovery do not necessarily permit a solution to be found by the learning system.”).

366. The statement quoted in *supra* note 364 is now famously known as the “obvious to try” rationale for finding obviousness. See *KSR Guidelines*, *supra* note 353, at 57,529 (defining the “obvious to try” rationale).

## B. LIMITATIONS OF THE CURRENT LEGAL FRAMEWORK FOR AI-ASSISTED INVENTIONS

While this Note suggests that the recommended AI-assisted practice described above<sup>367</sup> is the best choice available to satisfy the enablement and written description requirements with the least amount of experimentation, it unavoidably involves some uncertainties due to the limitations of the current legal framework for AI-assisted inventions.

### 1. False Dichotomy: Predictable and Unpredictable Arts

Although “predictability” was initially used as a term of degree in *In re Fisher*,<sup>368</sup> later cases typically use it as a qualitative term such that an art is either predictable or unpredictable, and then treat the art with different criteria accordingly.<sup>369</sup> This poses an AI-assisted invention an insuperable difficulty: If an AI is able to provide a solution with a 70% accuracy for a given problem, is this art predictable or unpredictable?

Instead of categorically determining an art as either predictable or unpredictable, this Note proposes the predictability of an art be described by its degree with respect to the impact on the amount of necessary experimentation. After all, the amount of necessary experimentation is what ultimately matters for enablement purposes.<sup>370</sup> For example, it is more instructive to say that for a genus of compounds with a common main structure, the property changed due to a given element attached at a certain site can be predicted with a 70% accuracy. This means that for a PHOSITA to be enabled to make and use seven species covered by the genus claim, the PHOSITA is expected to experiment with ten randomly selected species of the genus. Therefore, describing the predictability in such a way provides a more tangible sense of how the predictability factor affects whether the necessary experimentation is undue.

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367. See *supra* Section III.A.1 (providing this Note’s recommended practices).

368. *In re Fisher*, 427 F.2d 833, 839 (C.C.P.A. 1970).

369. See *supra* Section I.A.1.c. (citing cases that use predictability as a qualitative term).

370. See *In re Wright*, 999 F.2d 1557, 1561 (Fed. Cir. 1993) (“[T]o be enabling, the specification of a patent must teach those skilled in the art how to make and use the full scope of the claimed invention without ‘undue experimentation.’” (citations omitted)).

## 2. Unreasonable Test: Reasonable Amount of Routine Experimentation

But does a high predictability—say 99%—really help enablement under current law? Of course, 99% accuracy is not 100% accuracy. For a PHOSITA to practice the full scope of the claim, he or she would still need to experiment with all species in order to screen out the 1% that do not work. If the total number of covered species is large, say, ten thousand, with a hundred that do not work, is this claim enabled or not? On one hand, ten thousand experiments are too many according to *Gilead* and *Wyeth*.<sup>371</sup> On the other hand, the *Wands* court has also commented that a success rate of 44% for an antibody production method is “respectable” and enabling.<sup>372</sup> The only way to reconcile these cases is to notice that the success rate of experimentation in *Gilead* and *Wyeth* were supposed to be low or there was no clue of the success rate.<sup>373</sup> It is the potential large number of failed experiments that courts intend to police, not the experiments themselves. Otherwise, for genus claims that potentially cover inoperable species, to prohibit a large quantity of routine experimentation is equivalent to prohibiting a claim that is broad. But the breadth of a claim scope, by itself, is never a reason for invalidity.

The test based on a total experimentation amount is also ill-suited for how patents are practiced or infringed in the real world. If a patentee or a licensee<sup>374</sup> would like to practice the claimed invention, the patentee or licensee will likely practice only a few species in their interest. Similarly, for a copier to exert unjustifiable benefits from the disclosure of the patent, the copier only needs to find a few species that allow its business.

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371. See *supra* note 93.

372. *In re Wands*, 858 F.2d 731, 739 (Fed. Cir. 1988).

373. *Idenix Pharms. LLC v. Gilead Scis. Inc.*, 941 F.3d 1149, 1162 (Fed. Cir. 2019) (“[T]he [patent-at-issue] leaves a POSA searching for a needle in a haystack to determine which of the ‘large number’ of 2'-methyl-up nucleosides falls into the ‘small’ group of candidates that effectively treats HCV.” (citations omitted)); *Wyeth & Cordis Corp. v. Abbott Lab’ys*, 720 F.3d 1380, 1385 (Fed. Cir. 2013) (“Wyeth scientist confirmed the unpredictability of the art and the ensuing need to assay each candidate by testifying that, ‘until you test [compounds], you really can’t tell whether they work or not [*i.e.*, have antirestenotic effects].”).

374. The term “licensee” here refers to a person or an entity that can legally practice a patent under a patent license.

There is no compelling reason for one to attempt to practice all species covered by the claim at the same time.

It is obvious then that a more appropriate test is the average experimentation amount expected for practicing a randomly selected species. This test takes into account the effective proportion of the claimed genus and better fits with the reality of patent practice. It will not disrupt the expectations of the patent practice community because this test gives the same results should it be applied to past relevant cases.<sup>375</sup> More importantly, if this test is accepted by the PTO and courts, it can be claimed to a great certainty that the recommended AI-assisted patent practice will meet the enablement requirement given the present high accuracy of AI predictions.

### C. DEFENSE OF AI-ASSISTED PATENT PRACTICE

#### 1. This Practice Aligns with the Policy Purpose of Patent Law

As provided in the United States Constitution, patent law has been developed to “promote the Progress of Science and useful Arts, by securing for limited Times to Authors and Inventors the exclusive Right to their respective Writings and Discoveries . . . .”<sup>376</sup> It is a device for incentivizing the disclosure

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375. For example, if the experimentation success rate is expected to be low, such as what happened in *Gilead*, the average experimentation amount needed to find one effective species will be huge. Conversely, if the success rate is expected to be high, for example, 44% as in the facts in *Wands*, one can expect to perform about  $1/0.44 \cong 2.27$  experiments to find one effective species—obviously a small amount of experimentation. Moreover, just like the test based on total experimentation amount considers scenarios where experiments can be done in parallel, and where each species has to be synthesized before being tested, the proposed test based on average experimentation can also take these scenarios into account. See *Wands*, 858 F.2d at 740 (“[I]n the monoclonal antibody art it appears that an ‘experiment’ is not simply the screening of a single hybridoma, but is rather the entire attempt to make a monoclonal antibody against a particular antigen.”); *Gilead*, 941 F.3d at 1159 (“[M]any candidate nucleosides would need to be synthesized before they could be screened, as not all candidate nucleosides were available for purchase.”). If experimentation can be done in parallel, then the average experimentation amount is further compressed by a factor of the number of experiments that can be done simultaneously. Similarly, if some or all species need to be synthesized before testing, then the average experimentation amount should add the average time for synthesis.

376. U.S. CONST. art. I, § 8, cl. 8.

of innovations which might otherwise be kept secret or never exist due to threats of easy copying and imitating.<sup>377</sup>

However, the positive effects of patent law vary among different industries.<sup>378</sup> For example, “[i]n fast moving fields, such as electronics, semiconductor, and telecommunications, patents granted years after filing may be of ‘little value.’”<sup>379</sup> In contrast, empirical studies suggest that “patent protection was judged to be essential for . . . pharmaceuticals and chemicals” industries, among which, in pharmaceuticals industry, 65% of inventions would not have been introduced and 60% would not have been developed but for the existence of patent law system.<sup>380</sup> Accordingly, patent law is an essential mechanism to encourage the chemical and pharmaceutical industries, both of which are of the utmost importance to human welfare.

At the same time, the average cost of drug research and development is higher than ever.<sup>381</sup> As introduced above, current case law of the enablement and written description requirements is a great hurdle for genus claims in chemistry and biology arts to stand valid and can be discouraging to innovation in these industries.<sup>382</sup> Nevertheless, this ramification is mostly due to the large amount of prematurely-filed patents, and courts

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377. See *Bonito Boats, Inc. v. Thunder Craft Boats, Inc.*, 489 U.S. 141, 150–51 (1989) (“The federal patent system . . . embodies a carefully crafted bargain for encouraging the creation and disclosure of new, useful, and nonobvious advances in technology and design . . .”); see also KEVIN J. HICKEY, CONG. RSCH. SERV., R46525, *PATENT LAW: A HANDBOOK FOR CONGRESS* (2020) (“The patent system has long been viewed as important to encouraging American innovation by providing an incentive for inventors to create. Without a patent system, the reasoning goes, there would be little incentive for invention because anyone could freely copy the inventor’s innovation.”).

378. See generally Edwin Mansfield, *Patents and Innovation: An Empirical Study*, 32 *MGMT. SCI.* 173 (1986) (comparing different industries on how important they find patent protection to be).

379. FED. TRADE COMM’N, *TO PROMOTE INNOVATION: THE PROPER BALANCE OF COMPETITION AND PATENT LAW AND POLICY* 34–35 (2003) (citation omitted).

380. Mansfield, *supra* note 378, at 174–75; see also Bhaven N. Sampat, *A Survey of Empirical Evidence on Patents and Innovation*, 19–20 (Nat’l Bureau of Econ. Rsch., Working Paper No. 25383, 2018) (“The effects of patents on innovation incentives are stronger in some sectors (pharmaceuticals, chemicals) than others.”).

381. See generally Scannell et al., *supra* note 325, at 191 (explaining that research and development costs have increased steadily).

382. See *supra* Part I (describing the enablement and written description requirements and how they present hardship to genus claims in the traditionally unpredictable arts).

are resolved to strike down the prematurely-filed patents despite the potential discouraging impacts.<sup>383</sup>

Some have argued prematurely filed, or questionable patents in general, stifle follow-up research and incur social costs.<sup>384</sup> Presumably, such questionable patents are more common in arts related to chemistry and biology than others because the total experimentation from finding one effective species to confirming a whole effective genus is usually huge in these areas. Nevertheless, a claim is useful only if it covers adequate variations.<sup>385</sup> Filing a premature patent might be the only affordable way for entities in these industries to secure a bargaining chip against potential competitors.

AI is a gift from the latest development of big data techniques and computer science.<sup>386</sup> Its accurate predictions allow the chemistry and biology industries to file enabling patent applications without performing experiments on every species.<sup>387</sup> AI can affordably enhance patent quality in the traditionally unpredictable arts so that the negative impact of questionable patents are reduced, and the patent incentives for these arts can be restored to the “pre-*Lilly*” era.<sup>388</sup>

One might argue that the AI-assisted patent practice is allowing a patent to be a more accurate “hunting license,”<sup>389</sup> and

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383. *Ariad Pharm., Inc. v. Eli Lilly & Co.*, 598 F.3d 1336, 1353 (Fed. Cir. 2010) (“Ariad complains that [the written description requirement] disadvantages universities to the extent that basic research cannot be patented . . . That is no failure of the law’s interpretation, but its intention.”).

384. FED. TRADE COMM’N, *supra* note 379, at 187–88 (reporting arguments including “[i]f breadth is defined too broadly—that is, more broadly than is truly enabled—products that should be free to compete instead will infringe, and unwarranted market power may result,” and “broad initial patents may raise significant problems for follow-on innovation”).

385. *See supra* text accompanying notes 22–24 (explaining that narrow claims only provide limited protection, leading to an incentive to claim broadly).

386. *See Yang et al.*, *supra* note 154, at 10521–23 (introducing the history of AI).

387. *See generally supra* Part II (illustrating the potential utility of AI technology for patent seekers in chemistry and biology).

388. Many have argued that the decision of *Ariad Pharm., Inc. v. Eli Lilly & Co.*, 598 F.3d 1336 (Fed. Cir. 2010) has heightened the enablement and written description requirement for the traditionally unpredictable arts. *See, e.g.*, *Karshtedt et al.*, *supra* note 24, at 40–41.

389. *Brenner v. Manson*, 383 U.S. 519, 536 (1966) (“[A] patent is not a hunting license. It is not a reward for the search, but compensation for its successful conclusion.”); *see also Ebrahim*, *supra* note 44, at 596

unconfirmed predictions amount to “no more than a wish or plan.”<sup>390</sup> Such arguments ignore the fact that in the recommended practice,<sup>391</sup> at the very least the species deemed representative of the whole claimed genus are experimentally confirmed before filing the application.<sup>392</sup> Moreover, during the training process, the AI’s accuracy is validated by comparing its predictions with results from experiments.<sup>393</sup> The proposed practice reduces the total amount of experimentation in a rational and reliable way. AI enables the traditionally unpredictable arts to be more predictable, and thus these arts enjoy a similar, though not the same, benefit of the traditionally predictable arts.

## 2. Equity Concerns

Similar to other resources, while AI provides great benefits to the scientific community at large, it may also disadvantage solo inventors and small entities.<sup>394</sup> First, as discussed above, some AI tools and databases are not free,<sup>395</sup> and large companies have more financial resources to pay for them. Second, if developing AI using free databases and development tools, solo inventors and small entities are still disadvantaged because the whole AI training process, though made accessible by a plethora of educational resources, still requires significant expertise, skills, and time to complete.<sup>396</sup> A large company can afford to hire a professional group to perform the development process in a much shorter time. However, this is an unavoidable inequity

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(“[C]omputational research has made experimentation a ‘hunting license.’” (citation omitted)).

390. *Eli Lilly*, 598 F.3d at 1350 (citation and quotation mark omitted).

391. *See supra* Section III.A.1 (outlining recommended practices).

392. *See supra* Section III.A.1.b (recommending confirming AI prediction with some experiments).

393. *See supra* Section II.A.3 (introducing AI evaluation processes).

394. FED. TRADE COMM’N, *supra* note 379, at 83 (“[Economists] contend, large firms sponsoring considerable R&D can reduce the marginal costs of innovation by using ‘more specialized resources;’ can spread the fixed costs of any R&D over a wider base of output; can spread the risk of unsuccessful R&D efforts by sponsoring many R&D projects simultaneously; and have access to inexpensive investment capital, drawn from the firm itself or from capital markets.” (citation omitted)).

395. *See* discussion *supra* Section II.C.2 (discussing limitations on accessibility to some AI resources and tools).

396. *Id.*

existing in all cost-barricaded resources.<sup>397</sup> In an effort to reduce the general inequity in the patent application process, the PTO provides discounts to “small”<sup>398</sup> and “micro”<sup>399</sup> entities on various fees for patent applications.<sup>400</sup>

Specific to the potential unfairness caused by AI resources, this Note recommends that non-free AI tools and databases be removed from the toolkits of a PHOSITA, such that patents that are enabled only by the aid of commercially available AI resources should be considered non-enabled. Although this policy would not completely eliminate inequality related to AI resources, it would contribute to reducing it.

### CONCLUSION

Under current case law, the enablement and written description requirements pose considerable difficulties to genus claims in the traditionally unpredictable arts.<sup>401</sup> Regardless, many applicants are forced to file prematurely due to the need to protect their invented species and guard themselves against easy variations.<sup>402</sup> AI provides a promising solution to this dilemma. Scientists have been able to develop numerous AI that make reasonably accurate predictions for important problems in

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397. See *supra* note 394.

398. A small entity is any business entity that (1) does not confer any rights in the invention to an entity that does not qualify for the small entity status, 37 C.F.R. § 1.27, and (2) “[w]hose number of employees, including affiliates, does not exceed 500 persons.” 13 C.F.R. § 121.802.

399. A “micro entity” is “an applicant who makes a certification that the applicant—(1) qualifies as a small entity . . . ; (2) has not been named as an inventor on more than 4 previously filed patent applications . . . ; (3) did not . . . ha[ve] a gross income . . . 3 times the median household income . . . ;” and (4) does not confer any rights in the invention to an entity that does not qualify for the micro entity status, 35 U.S.C. § 123(a) (2011), or “an applicant who certifies that—(1) the applicant’s employer . . . is an institution of higher education . . . ; or (2) the applicant has [conferred his or her] ownership interest in the particular applications to such an institution of higher education.” 35 U.S.C. § 123(d).

400. Leahy-Smith America Invents Act, 35 U.S.C.A. § 10(b) (2011) (“The fees . . . for filing, searching, examining, issuing, appealing, and maintaining patent applications and patents shall be reduced by 50 percent with respect to the application of such fees to any small entity . . . , and shall be reduced by 75 percent with respect to the application of such fees to any micro entity . . .”).

401. See *supra* Sections I.A.1.c, I.B (outlining difficulties posed by enablement and written description requirements on genes claims in the traditionally unpredictable arts).

402. See *supra* Section III.C.1 (explaining the rationale for premature filing).

chemistry and biology.<sup>403</sup> Accordingly, this Note recommends that an applicant utilize AI predictions to rationally tailor the claim scope by reciting specific properties and/or functions and removing species that are unlikely to possess such properties and/or functions.<sup>404</sup> This Note further recommends that an applicant confirm the representative members of the claimed species by experiments.<sup>405</sup> A disclosure which includes experiment results of the presentative species, in addition to the guidance for making and using the rationally tailored claim, should satisfy the enablement and written description requirements.<sup>406</sup>

Although AI provides excellent predictions for the traditionally unpredictable arts, AI can hardly, if ever, be 100% accurate.<sup>407</sup> A predictability between zero and 100% cannot be readily categorized as predictable or unpredictable.<sup>408</sup> This shows the traditional dichotomy between predictable and unpredictable arts is inherently unable to encompass AI-assisted inventions. Accordingly, this Note proposes to abandon the coarse description of predictable and unpredictable arts, but rather dive into what predictability means to the quantity of necessary experimentation.<sup>409</sup>

Moreover, for technological areas that cannot be predicted 100% accurately by AI, which is almost always the case, increased predictability does not reduce the total amount of necessary experiments.<sup>410</sup> Under current case law, if the total amount of experiments is too great, regardless of any other factors, the invention is not enabled.<sup>411</sup> Hence, this Note argues

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403. See *supra* Section II.B (presenting examples in which AI makes great predictions for material engineering and drug discovery).

404. See *supra* Section III.A.1.a (outlining this Note's recommended tailoring practices within the claiming process).

405. See *supra* Section III.A.1.b (outlining further recommendations for applicants).

406. See *supra* Section I (outlining enablement and written description requirements).

407. See *supra* note 321 (explaining that AI tools can hardly be 100% accurate).

408. See *supra* Section III.B.1 (arguing the dichotomy of predictable and unpredictable arts is false).

409. *Id.*

410. See *supra* Section III.B.2 (discussing how increased predictability does not reduce the total amount of necessary experiments).

411. See *supra* Section I.A.1.d (outlining difficulties posed by the "total amount of experiment" standard).

that the total amount of experiments standard is unreasonable.<sup>412</sup> Instead, this Note proposes a test based on the average amount of necessary experiments to make and use a randomly selected species.<sup>413</sup> If this test is adopted, AI predictions could significantly reduce the average amount of necessary experiments, contributing greatly to enabling an invention.

This Note also argues the recommended patent practice aligns with the policy goal of patent law: to promote technological developments.<sup>414</sup> Patents encourage inventions in the chemical and pharmaceutical industries more than others.<sup>415</sup> The AI-assisted patent practice allows applicants to file patent applications after experimenting only some of the species of the claimed genus, which helps increase the incentive to innovate. The AI-assisted patent practice also does not circumvent the enablement and written description requirements because the reduced amount of experimentation is a result of rational choice, as the technological know-how is sufficiently disclosed to the public.<sup>416</sup>

Finally, this Note recommends non-free AI resources be removed from the toolkit of a PHOSITA so as to reduce inequity.<sup>417</sup> If this recommendation is adopted, AI can continue to bring the world enormous benefits with minimum inequity concerns.

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412. *See supra* Section III.B.2 (discussing the unreasonableness of the “total amount of experiment” standard).

413. *See id.* (outlining this Note’s recommended alternatives to current standard).

414. *See supra* Section III.C.1 (discussing patent law policy implications).

415. *See id.* (explaining the incentive to innovate created by patent rights).

416. *See id.* (explaining that the use of AI-assisted patent practice aligns with overarching policy goals).

417. *See supra* Section III.C.2 (recommending the discontinuation of the use of non-free AI resources from PHOSITA toolkits in the interest of reducing resource inequity).