

**Advancement of Artificial Intelligence in Chemical Sciences**

**Excellence Amaibiam Okonkwo<sup>1\*</sup>, Kennedy Izuchukwu Ogunwa<sup>1</sup>, and Linda Mgbo Ngumoha<sup>2</sup>**

<sup>1</sup>Department of Industrial and Medicinal Chemistry, David Umahi Federal University of Health Sciences Uburu-Ohaozara, Ebonyi State, Nigeria.

<sup>2</sup>Department of Chemistry, Alex Ekwueme Federal University, Ndifu-Alike Ikwo, Ebonyi State

**Corresponding Author's email:** [excelokonkwo@gmail.com](mailto:excelokonkwo@gmail.com); Phone: + 2348037737839

**ABSTRACT**

Artificial Intelligence (AI) is now being used in many areas of chemical sciences ranging from pharmaceutical chemistry, nanotechnology, analytical chemistry: faster and more precise compound identification in organic chemistry and easier complex organic synthesis. Integration of AI technologies in chemical sciences has enhanced reaction prediction, material design, drug discovery, and sustainability efforts. AI in chemical sciences has brought about a lot of transformation which is very essential for addressing global health, energy and environment challenges in line with sustainable development goals (SDGs). However, limitations such as data unavailability, difficult model interpretation, unreliability and scalability remain areas for further studies. This paper discusses the recent advancements, applications and future directions of AI in chemical sciences, highlighting its roles in shaping the future of chemical sciences.

**KEYWORDS:** Artificial Intelligence (AI), Chemical Sciences, Drug Discovery, Sustainability, Reaction Prediction.

**1. INTRODUCTION**

Artificial Intelligence is a field in computer science that is capable of performing tasks commonly associated with intelligent beings. It is programmed to carry out very complex tasks with great proficiency. It has emerged as developmental tool across numerous scientific disciplines of which chemical sciences is not an exception. The integration of artificial intelligence (AI) into the chemical sciences marks a paradigm shift in how chemistry is studied, understood, and applied.<sup>1</sup> The field has evolved from hypothesis-driven experimentation to data-driven discovery powered by computational intelligence.<sup>2</sup> A surge in AI-based research and tools have led to major advancements in various areas of chemistry, significantly, facilitating breakthroughs in molecular modeling, drug discovery, materials design, catalysis, environmental chemistry and beyond.<sup>3</sup> This sudden increase has been driven by the proliferation of large chemical datasets, advances in computational power, and the development of sophisticated algorithms capable of learning and predicting complex chemical phenomena.<sup>4</sup>

AI employs a lot of methods particularly machine learning (ML), deep learning (DL), neural networks, and natural language processing (NLP) which have enabled chemists to extract patterns from vast data repositories, automate experimental procedures, and design new molecules with unprecedented accuracy and efficiency.<sup>1,5,6</sup> These have caused changes to how chemists think about reaction mechanisms, molecular property prediction, and laboratory automation.<sup>7</sup> As AI continues to mature, its integration with chemical sciences is expected to deepen, potentially redefining the discipline's theoretical foundations and experimental methodologies. AI is becoming relevant in research, and very likely chemists that don't embrace it will be heavily disadvantaged.

Recent studies illustrate how AI has enhanced various areas of chemical sciences. In drug discovery, for instance, generative models have been used to propose novel drug candidates with desired active compounds and toxicity profiles, dramatically reducing the cost and time of development.<sup>8,9</sup> In catalysis, AI has facilitated the identification of optimal catalyst compositions and reaction conditions.<sup>10,11</sup> Similarly, materials informatics now leverages AI for the design of energy storage materials, semiconductors, and polymers with tailored properties.<sup>12</sup> AI stands as a key enabler in solving complex chemical problems and achieving the Sustainable Development Goals.<sup>1,6</sup>

Despite these advances, several challenges persist. Issues of data quality, impact of AI on jobs, inability of a human to understand a model's inner workings and reasoning process and the need for interdisciplinary collaboration continue to shape the discourse around AI in chemistry.<sup>13</sup> Another key

---

**Abuja, Nigeria - May 4-7, 2025**

concern is on ethical considerations and the integration of AI into traditional laboratory practices. This paper summarizes recent advancements, applications, and future directions of AI in chemical sciences. It highlights the developmental potential of AI in driving innovation, improving research efficiency, and addressing longstanding challenges in the field.

## **2. METHODS**

Research methods are a scientific way to obtain data with specific purposes and uses.<sup>14</sup> The method used in this research is descriptive qualitative which involves looking at several previous studies related to the research topic.<sup>15</sup>

## **3. ADVANCEMENTS AND APPLICATIONS OF ARTIFICIAL INTELLIGENCE IN CHEMICAL SCIENCES**

The advancements and application of artificial intelligence (AI) have paved the way to a new era in learning of chemical sciences. Artificial Intelligence (AI) techniques are becoming valuable due to several reasons like easy to learn and use, simple implementation, easy designing, effectiveness, robustness, and flexibility; they are widely used in various areas of chemistry including molecular design, molecular property prediction, retro synthesis, reaction outcome prediction and reaction conditions prediction.<sup>16</sup> AI technology gives an avenue to process large chemical data with high accuracy, predict molecular properties with precision, and design new molecules efficiently with the help of artificial neural networks, evolutionary algorithms and fuzzy logic. Artificial Intelligence (AI) has become the main catalyst in drastic transformation in various fields of chemical sciences. It has opened the door to significant changes in the way we understand, analyze, and apply knowledge about the molecular structure, reactivity, and design of chemicals and has been widely applied in core domains of chemical sciences.

### **3.1 Chemical Science Education**

In the context of chemical sciences, AI has opened the door to significant changes in the way we understand, analyze, and apply knowledge about the molecular structure, reactivity, and design of chemicals.<sup>17</sup> Teachers are desperate to be creative and innovative in teaching at this 21st-century era because they are faced with the challenges of producing students who are ready to face the reality in a developing world.<sup>18</sup> Artificial intelligence help students have better access to an enhanced personalized learning tool. AI technology has been a key in accelerating chemical research and has paved the way for breakthroughs in innovations that have change the paradigm in chemical sciences as a whole. Thus, AI can be a very useful tool in supporting the teaching and learning process of chemical sciences, allowing students to explore and understand difficult concepts in a more engaging and interactive way.<sup>17</sup>

### **3.2 Molecular Property Prediction**

AI is able to accurately predict chemical properties based on molecular structure. With the integration of AI algorithms into structure modeling, chemical scientists can design molecular structures faster and more efficiently, speeding up the process of research and development of new chemicals for drug production.<sup>19</sup> The article "Chemception: A Deep Neural Network with Minimal Chemistry Knowledge matches the Performance of Expert-developed Quantitative Structure-Activity Relationship/Quantitative Structure-Property Relationship (QSPR) Models published in arXiv in 2017.<sup>20</sup> Machine learning algorithms such as support vector machines (SVMs), random forests (RF), and deep neural networks (DNNs) have also been employed for predicting molecular properties such as solubility, boiling point, and reactivity, a proof that technology makes chemistry easier to learn.<sup>1,21</sup>

---

**Abuja, Nigeria - May 4-7, 2025**

### 3.3 Reaction Outcome and Retrosynthesis

Retrosynthesis is a key process in organic chemistry that is used to determine the synthesis pathway from complex molecules to simpler molecules.<sup>22</sup> AI tools like IBM's RXN for Chemistry and MIT's Molecular Transformer model predict reaction outcomes and automate retrosynthetic pathway planning.<sup>23,24</sup> The work of Segler and Waller also show progress in modeling chemical reactions using this approach of machine learning which could have major implications in the understanding and design of molecular synthesis processes in organic chemistry. These researches reduce the need for trial-and-error approaches in organic synthesis.<sup>25</sup>

### 3.4 Chemical Process Optimization

AI having better prediction and modeling capabilities can help in optimizing chemical processes and improving production efficiency and product quality. The combination of AI and chemical sciences unlock the potential for breakthroughs in its understanding and applications thereby increasing the ability to design new molecules, predict chemical properties, and increase the efficiency of research and development in chemical sciences.<sup>1, 26, 27</sup>

### 3.5 Material Discovery

AI is transforming the discovery of materials by accelerating the process of finding new materials with desired properties.<sup>1</sup> Machine learning and high-throughput screening are enabling researchers to predict material behavior, optimize designs, and discover new materials faster and more efficiently than traditional methods.<sup>28</sup> This shift is crucial for addressing global challenges, accelerating the discovery of new materials like catalysts, polymers, and battery components and by analyzing large chemical datasets to predict novel combinations.<sup>1</sup> A typical example of AI used for material discovery is MatterGen, it works by generating novel materials, giving prompts of the design requirements for an application instead of screening the candidate thus enhancing advance development with improved characterization and autonomous experimentation.<sup>29</sup>

### 3.6 Reduction of Reliance on Experimentation

AI predictive capacity can help reduce repetitive experiments, saving time and resources in chemical research. This approach aims to automatically create new molecules with desired properties based on a continuous representation of the molecular structure.<sup>30, 31</sup>

### 3.7 Drug Discovery and Development

AI facilitates drug candidate screening, QSAR modeling, and toxicity prediction, significantly reducing the cost and time for drug development.<sup>32</sup> Artificial Intelligence (AI) is revolutionizing traditional drug discovery and development models by seamlessly integrating data, computational power, and algorithms. This synergy enhances the efficiency, accuracy, and success rates of drug research, shortens development timelines, and reduces costs.<sup>33</sup> Coupled with machine learning (ML) and deep learning (DL), AI has demonstrated significant advancements across various domains, including drug characterization, target discovery and validation; small molecule drug design, and the acceleration of clinical trials. Through molecular generation techniques, AI facilitates the creation of novel drug molecules, predicting their properties and activities, while virtual screening optimizes drug candidates. Additionally, AI enhances clinical trial efficiency by predicting outcomes, designing trials, and enabling drug repositioning. Majority of pharmaceutical companies have used AI to improve drug discovery. Verge Genomics uses AI to predict the effects of some new drugs on patients with Alzheimer's disease and Parkinson's disease.<sup>34</sup> In 2018, Bayer and Merck received Food and Drug Administration approval to use AI algorithms to support clinical decision making for chronic thromboembolic pulmonary hypertension.<sup>1,35</sup> Novartis currently uses AI algorithms to classify digital images of different cells.<sup>36</sup> In 2018, the biotech company Cyclica collaborated with Bayer, using AI machine learning to determine the polypharmacological profiles of small molecules and develop more affordable drugs.<sup>37</sup>

### 3.8 Spectroscopy and Analytical Chemistry

In recent years, artificial intelligence (AI) has offered transformative solutions to enhance the speed, accuracy, and efficiency of spectroscopic analysis. AI is revolutionizing the use of spectroscopy in fields like pharmaceuticals, materials science, and environmental monitoring.<sup>38</sup> AI has helped to improve the accuracy of spectroscopic analysis by training algorithms to consistently detect discrepancies in spectral data, reducing the chances of misinterpretation, which is particularly relevant in industries like pharmaceuticals, where ensuring the quality and safety of products is paramount. AI improves spectral analysis (NMR, IR, MS) by automating peak identification, baseline correction, and compound classification.<sup>39</sup>.

## 4. IMPACT OF AI ON GLOBAL CHALLENGES AND THE SUSTAINABLE DEVELOPMENT GOALS (SDGs)

AI serves as a catalyst for achieving the SDGs by providing innovative, data-driven solutions to some of the world's most pressing challenges. AI's integration into chemical sciences supports various global challenges in different ways. Its integration across sectors is significantly influencing key areas, particularly **SDG 3 (Good Health and Well-being)**<sup>40,41,42</sup>; **SDG 6 (Clean Water and Sanitation)**<sup>43,44</sup>; **SDG 7 (Affordable and Clean Energy)**<sup>45</sup>; **SDG 12 (Responsible Consumption and Production)**<sup>46</sup>; and **SDG 13 (Climate Action)**<sup>47</sup>.

## 5. CHALLENGES AND LIMITATIONS OF AI IN CHEMICAL SCIENCES

Despite its advantages, AI has brought a tremendous change to chemical sciences and this has positively affected most of the global challenges however limitations are inevitable and they include the following: data scarcity and quality issues.<sup>4,33,48</sup>; inability of understanding AI results in a chemical context and integrating them with existing chemical knowledge; ethical, legal, and regulatory compliance<sup>49</sup>; computational cost and infrastructure<sup>39</sup>; insecurity of data in chemical research; unfriendly AI platforms<sup>1</sup>; training of AI models on narrow data set<sup>3</sup>; limitations of AI Algorithms in understanding complex patterns in chemical data and difficult interpretation of models and transparency.<sup>50</sup>

## 6. FUTURE DIRECTIONS OF AI TO CHEMICAL SCIENCES

The future development of chemical knowledge and AI technologies are likely to cause challenges to AI in chemical sciences thus a huge need for collaborations among chemists, computer scientist and AI experts to ensure constant update of AI models. This will directly improve interpretability, ensuring safety and ethics in the application of artificial intelligence thereby enhancing increased autonomy, sustainability, and deeper integration with emerging technologies. Among the developments, the emergence of autonomous laboratories, or self-driving experimental platforms, capable of designing, executing, and optimizing chemical experiments with minimal human intervention thereby accelerating discovery and reducing costs is very significant. Explainable AI (XAI), which focuses on creating interpretable models that reveal underlying chemical reasoning, fostering trust and adoption, particularly in high-stakes domains such as drug discovery and toxicology remains another key trend.<sup>50</sup> The integration of AI with quantum computing is also expected to revolutionize molecular modeling and reaction prediction by enabling more efficient analysis of complex quantum systems.<sup>52</sup> Moreover, enhanced data infrastructure will be critical for the accuracy and reproducibility of AI models, with increasing emphasis on standardized, high-quality, and openly accessible datasets aligned with FAIR (Findable, Accessible, Interoperable, and Reusable) principles<sup>53</sup>. AI will further green and sustainable chemistry by aiding in the design of environmentally friendly materials and energy-efficient processes, thereby supporting circular economy practices and climate goals.<sup>7</sup> In addition, multimodal and multi-scale integration will allow AI systems to combine diverse data types such as text, spectra, and molecular structures across scales from the molecular to the process level, enabling more comprehensive chemical modeling.<sup>39</sup> Finally, the application of AI in education and collaborative research will democratize access to chemical knowledge and foster interdisciplinary innovation.<sup>25</sup>

## 7. CONCLUSION

The integration of artificial intelligence into chemical sciences represents a critical advancement in the 21st century. With applications ranging from drug discovery to environmental sustainability, AI offers powerful tools to address both long-standing and emerging challenges. However, to fully harness its potential, the chemical sciences community must overcome existing limitations in data quality, model transparency, and interdisciplinary collaboration. As AI continues to evolve, it is expected to redefine the boundaries of chemical research and contribute significantly to achieving global sustainability goals.

## CONFLICT OF INTERESTS

The authors declare no conflict of interests.

## REFERENCES

- (1) Butler, K. T.; Davies, D. W.; Cartright, H.; Isayev, O.; Welsh, Aron. Machine Learning for Molecular and Materials Science. *Nature*, **2018**, 559(7715), 547–555.
- (2) Mater, Adam C.; Coote, Michelle L. Deep Learning in Chemistry. In: *Journal of Chemical Information and Modeling*. **2019**, Vol.59, No.6. pp.2545-2
- (3) Schneider, Sascha.; Beege Maik.; Nebel, Steve.: Rey, G.D. A meta-analysis of how signaling affects learning with media. *Educational Research Review* **2017**. 23 DOI: 10.1016/j.11.001
- (4) Zeller, M.; Friedler, S.A.; Joshua, S.; Norquist, A. J. Machine-Learning-Assisted Materials Discovery Using Failed Experiments. *Nature*, **2016**, 533(7601), 73–76.
- (5) Sanchez-Lengeling, B.; Outeiral, C.; Guimaraes, G.; AspuruGuzik, A. Optimizing Distributions over Molecular Space. An Objective-Reinforced Generative Adversarial Network for InverseDesign Chemistry (Organic). *ChemRxiv*. Preprint, **2017** DOI: 10.26434/chemrxiv.5309668.v3
- (6) Aspuru-Guzik, A.; Tim, B.; Varinia, B.; Philip, C.; Biggin, F. B.; Itamar, B. J.; Ksenia, R.; Briling, et al. "Discovering chemical structure: general discussion." *Faraday Discussions*, vol. 256, **2025**, pp. 177-220.
- (7) Schwaller, P.; Probst, D.; Vaucher A.C.; Nair , V.; Kreutter, D.; Laino, T. Mapping the Space of Chemical Reactions Using Attention-Based Neural Networks. *Nature Machine Intelligence*, (8) Zhavoronkov, A.; Aspuru-Guzik, A. Reply to 'Assessing the impact of generative AI on medicinal chemistry'. *Nat. Biotechnol.* 2020. 38, 146
- (9) Gangwal, A.; Ansari, A.; Ahmad, I.; Azad, AK.; Kumarasamy, V.; Subramaniyan, V.; Wong, L.S. Generative artificial intelligence in drug discovery: basic framework, recent advances, challenges, and opportunities. *Front Pharmacol.* **2024**;15:1331062.
- (10) Mazheika, A.;Wang, Y.G.; Valero, R.; Viñes, F.; Illas, F.; Ghiringhelli, L..; Levchenko, S.V.; Scheffler, M. Artificial-intelligence-driven discovery of catalyst genes with application to CO<sub>2</sub> activation on semiconductor oxides. *Nat Commun.* **2022** ;13(1):419.
- (11) Morán-González, L.; Burnage, A.L.; Nova, A.; Balcells, D. AI Approaches to Homogeneous Catalysis with Transition Metal Complexes. *ACS Catal.* 2025 15(11):9089-9105
- (12) Nematov, D.; Hojamberdiev, M. *Machine Learning-Driven Materials Discovery: Unlocking Next-Generation Functional Materials – A Minireview*. *arXiv* 2025, arXiv:2503.18975.
- (13) Hrckova, A.; Renoux, J.; Tolosana Calasanz, R.; Chuda, D.; Tamajka, M.; Simko, J. AI Research Is Not Magic, It Has To Be Reproducible and Responsible: Challenges in the AI Field from the Perspective of Its PhD Students. *arXiv*. 2024, arXiv:2408.06847.
- (14) Creswell, J. W.; Creswell, J. D. *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*, 5th ed.; Sage Publications: Thousand Oaks, CA, **2018**.
- (15) Nassaji, H. Qualitative and descriptive research: Data type versus data analysis. *Language Teaching Research*. **2015**, 19(2), 129–132.

(16) UKCI. *Advances in Intelligent Systems and Computing*, vol 1453. *Springer*. **2023**, Cham.

(17) Tasneem, S.; Saman, J. AI in Senior Chemistry Education: Enhancing engagement, Personalization and Pedagogical Practice. *Journal of Media Horizons* **2025**, 6 (2), 112-124.

(18) Iyamuremye, A., Niyonzima, F.N., Mukiza, J. *et al.* Utilization of artificial intelligence and machine learning in chemistry education: a critical review. *Discov Educ.* **2024** 3, 95.

(19) Kokudeva, M.; Vichev, M.; Naseva, E.; Miteva, D.G.; Velikova, T. Artificial intelligence as a tool in drug discovery and development. *World J Exp Med.* **2024** 20;14(3):96042.

(20) Kearnes, S.; McCloskey, K.; Berndl, M.; Pande, V.; Riley, P. *Chemception: A Deep Neural Network with Minimal Chemistry Knowledge Matches the Performance of Expert-Developed Quantitative Structure–Activity Relationship (QSAR) / Quantitative Structure–Property Relationship (QSPR) Models*. *arXiv* **2017**, arXiv:1706.06689.

(21) Schütt, K. T.; Kindermans, P.-J.; Sauceda, H. E.; Chmiela, S.; Tkatchenko, A.; Müller, K.-R. *Quantum-Chemical Insights from Deep Tensor Neural Networks*. *Nat. Commun.* **2017**, 8 (1), 13890.

(22) Segler, M. H. S.; Waller, M. P. *Neural-Symbolic Machine Learning for Retrosynthesis and Reaction Prediction*. *Chem.–Eur. J.* **2017**, 23 (25), 5966–5971.

(23) Schwaller, P.; Vaucher, A. C.; Laino, T.; Reymond, J. L. *Prediction of Chemical Reaction Yields Using Deep Learning*. *Mach. Learn.: Sci. Technol.* **2021**, 2 (1), 015016. .

(24) Schwaller, P.; Laino, T.; Gaudin, T.; Bolgar, P.; Hunter, C. A.; Bekas, C.; Lee, A. A. *Molecular Transformer: A Model for Uncertainty-Calibrated Chemical Reaction Prediction*. *ACS Cent. Sci.* **2019**, 5 (9), 1572–1583.

(25) Segler, M. H. S.; Preuss, M.; Waller, M. P. *Planning Chemical Syntheses with Deep Neural Networks and Symbolic AI*. *Nature*. **2018**, 555 (7698), 604–610. Sanchez-Lengeling, B.; AspuruGuzik, A. *Engineering*. *Science* **2018**, 361 (6400), 360–365.

(26) Sanchez-Lengeling, B.; Aspuru-Guzik, A. *Engineering*. *Science* **2018**, 361 (6400), 360–365.

(27) Häse, F.; Roch, L. M.; Aspuru-Guzik, A. *Next-Generation Experimentation with Self-Driving Laboratories*. *Trends Chem.* **2019**, 1 (3), 282–291.

(28) Schmidt, J.; Marques, M. R. G.; Botti, S.; Marques, M. A. L. Recent Advances and Applications of Machine Learning in Solid-State Materials Science. *npj Comput. Mater.* **2019**, 5 (1), 83.

(29) Stach, E.; DeCost, B.; Kusne, A. G.; Harrington, T.; Schrier, J.; Billinge, S. J. L.; Buonassisi, T.; Foster, I.; Hattrick-Simpers, J.; Mehta, A.; Montoya, J.; Olivetti, E.; Park, C.; Rotenberg, E.; Saal, J.; Smullin, S.; Srinivasan, V.; Suram, S. K.; Tabor, D. P. Autonomous Experimentation Systems for Materials Development: A Community Perspective. *Matter*. **2021**, 4 (9), 2702–2726.

(30) Gowda, S.; Tran, R.; Yang, J.; Zhang, Y.; Xu, Q.; Wood, B. C.; Wolverton, C.; Ong, S. P. MatterGen: A Generative Model for Inverse Materials Design. *npj Comput. Mater.* **2024**, 10, 35.

(31) Gómez-Bombarelli, R.; Wei, J. N.; Duvenaud, D.; Hernández-Lobato, J. M.; Sánchez-Lengeling, B.; Sheberla, D.; Aguilera-Iparraguirre, J.; Hirzel, T. D.; Adams, R. P.; Aspuru-Guzik, A. Automatic Chemical Design Using a Data-Driven Continuous Representation of Molecules. *ACS Cent. Sci.* **2018**, 4 (2), 268–276.

(32) Stokes, J. M.; Yang, K.; Swanson, K.; Jin, W.; Cubillos-Ruiz, A.; Donghia, N. M.; MacNair, C. R.; French, S.; Carfrae, L. A.; Bloom-Ackermann, Z.; Tran, V. M.; Chiappino-Pepe, A.; Badran, A. H.; Andrews, I. W.; Chory, E. J.; Church, G. M.; Brown, E. D.; Jaakkola, T. S.; Barzilay, R.; Collins, J. J. A Deep Learning Approach to Antibiotic Discovery. *Cell*. **2020**, 180 (4), 688–702.e13.

(33) Fu, C. Artificial Intelligence for Drug Discovery and Development. *Acta Pharm. Sin. B* **2022**, 12 (10), 3607–3616.

(34) Verge Genomics. Verge Genomics Uses AI to Tackle Neurodegenerative Diseases. *Verge Genomics* (accessed Aug 27, 2. U.S. Food & Drug Administration. FDA Permits Marketing of First AI-Based Device to Detect Certain Heart Problems. *FDA News Release* (2018).

(35) . U.S. Food & Drug Administration. FDA Permits Marketing of First AI-Based Device to Detect Certain Heart Problems

(36) Novartis. Harnessing Artificial Intelligence to Transform Drug Discovery. *Novartis* (accessed Aug 27, 2025).

(37) Cyclica. Cyclica and Bayer Partner to Apply AI in Drug Discovery. *Cyclica Press Release*

(2018). <https://www.cyclicarx.com>

(38) Chen, J.; McCallum, A.; Achim, A.; He, Y. Artificial Intelligence in Spectroscopy: From Peak Assignment to Automated Spectral Interpretation. *TrAC Trends Anal. Chem.* **2021**, 143, 116370.

(39) Zhou, Z.; Smith, A.; Johnson, B.; Patel, C.; Wang, D.; Martinez, E.; Gupta, F. AI-Driven Spectroscopy for Real-Time Chemical Analysis. *Anal. Chem.* **2022**, 94 (2), 789–796.

(40) Zhavoronkov, A., et al. Deep Learning Enables Rapid Identification of Potent DDR1 Kinase Inhibitors. *Nature Biotechnology*, **2019**, 37(9), 1038–1040.

(41) Topol, E. *Deep Medicine: How Artificial Intelligence Can Make Healthcare Human Again*; Basic Books: New York, **2019**. ISBN 9781541644632.

(42) Guégan J-F, Suzán G, Kati-Coulibaly S, Bonpamgue DN, Moatti J-P. Sustainable Development Goal 3, “health and well-being”, and the need for more integrative thinking. *Veterinaria México OA*. **2018**,;5(2).doi:10.21753/vmoa.5.2.443

(43) Zou, S.; Ju, H.; Zhang, J. Water Quality Management in the Age of AI: Applications, Challenges, and Prospects. *Water* **2025**, 17, 1641

(44) Jayakumar, D.; Bouhoula, A.; Al-Zubari, W.K. Unlocking the Potential of Artificial Intelligence for Sustainable Water Management Focusing Operational Applications. *Water* **2024**, 16, 3328.

(45) Razak, T. R.; Ismail, M. H.; Darus, M. Y.; Jarimi, H.; Su, Y. Artificial Intelligence in Renewable Energy: A Systematic Review of Trends in Solar, Wind, and Smart Grid Applications. *Research and Reviews in Sustainability* **2025**, Vol 1, No 1, p 1-22.

(46) United Nations. *Sustainable Development Goal 12: Ensure Sustainable Consumption and Production Patterns*. United Nations, **2015**. Available online: <https://sdgs.un.org/goals/goal12> (accessed Aug 30, 2025).

(47) Rolnick, D.; Donti, P. L.; Kaack, L. H.; Kochanski, K.; Lacoste, A.; Sankaran, K.; Ross, A. S.; Milojevic-Dupont, N.; Jaques, N.; Waldman-Brown, A.; Luccioni, A.; Maharaj, T.; Sherwin, E. D.; Mukkavilli, S. K.; Kording, K. P.; Gomes, C.; Ng, A. Y.; Hassabis, D.; Platt, J. C.; Creutzig, F.; Chayes, J.; Bengio, Y. Tackling Climate Change with Machine Learning. *arXiv* [Preprint], arXiv:1906.05433, **2019**.

(48) Wu, Z.; Ramsundar, B.; Feinberg, E. N.; Gomes, J.; Geniesse, C.; Pappu, A. S.; Leswing, K.; Pande, V. MoleculeNet: A Benchmark for Molecular Machine Learning. *Chem. Sci.* **2018**, 9 (2), 513–530.

(49) Coley, C. W.; Eyke, N. S.; Jensen, K. F. Autonomous Discovery in the Chemical Sciences Part I: Progress. *Angew. Chem. Int. Ed.* **2020**, 59 (51), 22858–22893.

(50) Samek, W., et al. Explainable Artificial Intelligence: Understanding, Visualizing and Interpreting Deep Learning Models. *IEEE Signal Processing Magazine*, **2021**, 38(3), 88–92.

(51) Burger, B.; Maffettone, P. M.; Gusev, V.V.; Aitchison, C. M.; Bai, Y.; Wang, X.; Li, X.; Alston, B. M.; Li, Bi; Clowes, R.; Rankin, N.; Harris, B.; Sprick, R. S.; Cooper, A. I. A Mobile Robotic Chemist. *Nature* **2020**, 583 (7815), 237–241.

(52) Cao, Y.; Romero, J.; Olson, J. P.; Degroote, M.; Johnson, P. D.; Kieferová, M.; Kivlichan, I. D.; Menke, T.; Peropadre, B.; Sawaya, N. P. D.; Sim, S.; Veis, L.; Aspuru-Guzik, A. Quantum Chemistry in the Age of Quantum Computing. *Chem. Rev.* **2019**, 119 (19), 10856–10915.

(53) Wilkinson et al., The FAIR Guiding Principles for Scientific Data Management and Stewardship. *Sci. Data*. **2016**, 3, 160018. .