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Review

NEXT GENERATION OF PHARMACEUTICAL ANALYTICAL TECHNIQUES

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Abstract

This document explores the transformative impact of Artificial Intelligence (AI) and technological downsizing on the pharmaceutical and analytical industries. artificial intelligence refers to the ability of machine learning systems to carry out cognitive tasks, including visual perception ,reasoning ,learning ,and decision making, is vital for managing the large datasets generated by data digitalization in pharmaceuticals. Using advanced tools and networks, core AI technologies like Machine Learning (ML) and Deep Learning (DL) replicate human cognitive abilities. artificial intelligence plays a role at every phase of the pharmaceutical product life cycle, including drug discovery (finding compounds, verifying targets, and optimizing structure), clinical trial design (patient selection and adherence monitoring), manufacturing (quality control, customized dosing), and product management.

Simultaneously, technological miniaturization, driven by power-efficient designs, breakthroughs in semiconductor technology, and microfabrication procedures, is transforming analytical processes. Significant advantages of miniaturization include lowering the quantity of the sample needed, using fewer chemicals and solvents, cutting waste, boosting portability and power economy, improving sensitivity, and increasing speed (sample throughput). While practically every stage of the analytical process has been reduced, detection and data processing have attained an excellent degree of downsizing. In essence, the convergence of powerful AI capabilities and breakthrough miniaturized technologies is opening the path for more efficient, precise, and sustainable procedures throughout drug development and analytical research.

Keywords: Artificial Intelligence, cognitive tasks, including visual perception, reasoning, learning and decision making, Machine Learning (ML) and Deep Learning (DL), human cognitive abilities, power-efficient designs, breakthroughs in semiconductor technology, and microfabrication procedures.

INTRODUCTION

Robotics relies heavily on deep learning (DL), machine learning (ML), and artificial intelligence (AI) (1). The ability of a machine to perform tasks that often require human intellect, like speech recognition, natural language comprehension, and decision-making, is referred to as artificial intelligence (AI). With the help of AI , robots can perceive and interact with their environment, make decisions, and complete challenging jobs. (2). A subfield of artificial intelligence called "machine learning" employs algorithms to enable robots to learn from data and improve over time (3). Artificial neural networks are employed in deep learning, a M. Soori, B. Arezoo and R. Dastres Cognitive Robotics 3 (2023) 54–70 type of machine learning (ML), to enable computers learn from enormous amounts of data (4).However, when these procedures reached higher degrees of maturity, it became increasingly obvious that sample preparation remains critical, dictating the success and reliability of any analytical procedure, despite the advanced nature of the instruments. The sample preparation process, particularly the extraction step, plays a crucial role in establishing the precision and reliability of the analysis of target compounds. This stage is critical for removing matrix interferences, separating, and concentrating analytes, ensuring high-quality results.

Artificial Intelligence (AI) has been recognised as one of the most recent, essential advancements of the convergence in electronic markets (5) and has become an increasingly relevant topic for information systems (IS) research (6);(7) While most of the literature focuses on creating AI that can replicate and replace people (8);(9) IS research in general and decision support systems (DSS) research in particular highlight how AI may help humans (10).A possible route for combining AI research from several domains is provided by recent studies in hybrid intelligence (HI) and human-AI cooperation (11).

THINGS TO KNOW ABOUT ARTIFICIAL INTELLIGENCE

The pharmaceutical industry has seen a sharp rise in data digitization in recent years. The difficulty of gathering, analyzing, and using that knowledge to address challenging healthcare issues is a result of this digitalization (12). This encourages the application of AI, because it can manage massive volumes of data with greater automation (13). AI is a technology-based system that mimics human intellect through a variety of sophisticated tools and networks. Nevertheless, it does not pose a risk of full substitution for human physical involvement (14);(15).

Recent AI definitions transfer the human intelligence idea to machines in its entirety as “the ability of a machine to perform cognitive functions that we identify with human minds, such as perceiving, reasoning, learning, interacting with the environment, problem solving, decision-making, and even exhibiting creativity” (16) The Turing test (17). can be used to determine if AI instantiations can execute human tasks at least as well as humans (18). Finally, the AI is viewed by the rational agent stream as either an intelligent (19) or reasonable (20) agent. 3 In addition to acting independently, this agent aims to achieve the rationally optimal result.

LEARNING MACHINES

ML is seen by several academics as a (sole) component of AI (21) (22) (23) In general, learning is an essential element of human cognition (24) In order to better comprehend incoming information, humans use abstract knowledge to digest large amounts of data.

The model can learn "on its own," meaning that no manual modification or programming of rules or problem-solving techniques is needed during the learning process. More specifically, supervised machine learning techniques always seek to develop a model by using an algorithm on a collection of known data points in order to obtain understanding of an unknown set of data (25).

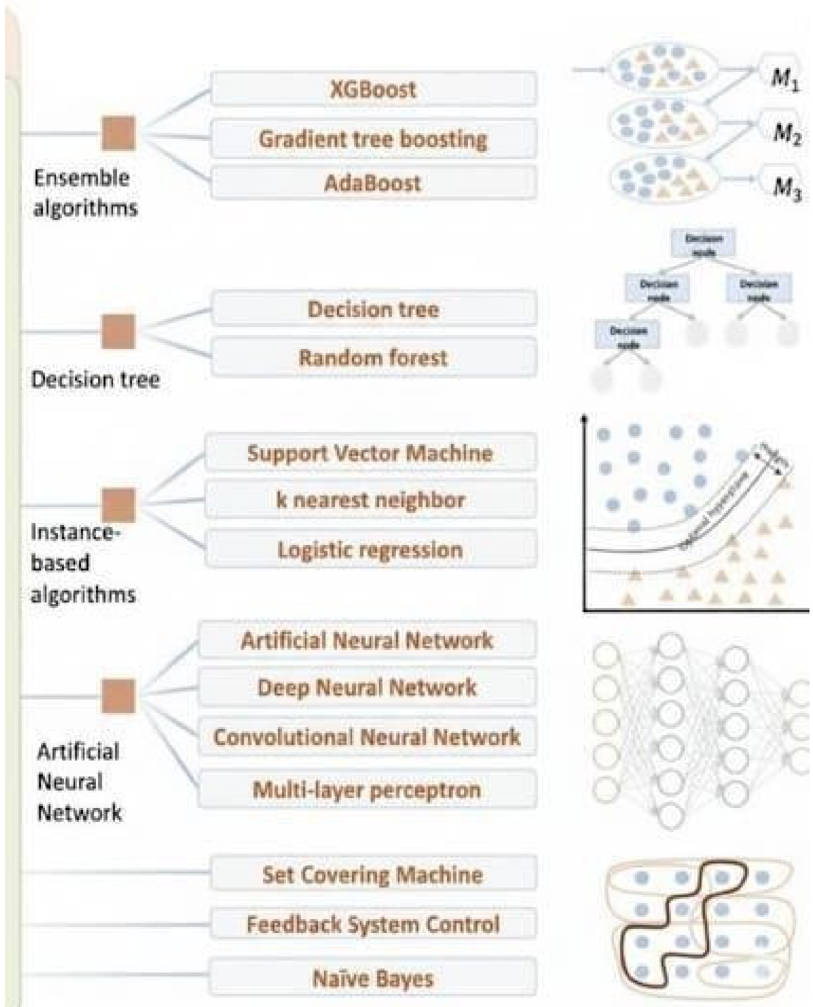


Fig.1 Drug delivery using machine learning algorithms is utilised to treat infectious disease(26).

AI IN PHARMACEUTICAL PRODUCT LIFECYCLES

Given that AI can support rational drug design (27). aid in decision-making, determine the most appropriate therapeutic strategy for a patient , including customized medications, and manage the clinical data generated and use it for future drug development (28), it is possible to envision its involvement in the development of a pharmaceutical product from the bench to the bedside. Eularis created E-VAI, an analytical and decision-making AI platform that predicts important factors in pharmaceutical sales by using ML algorithms and an intuitive user interface to create analytical roadmaps based on competitors, important stakeholders, and currently held market share (29) thus assisting marketing leaders to allocate resources for optimal market share gain, reversing poor sales and enabled them to forecast where to make investments. Various uses of AI in the creation and discovery of drug.

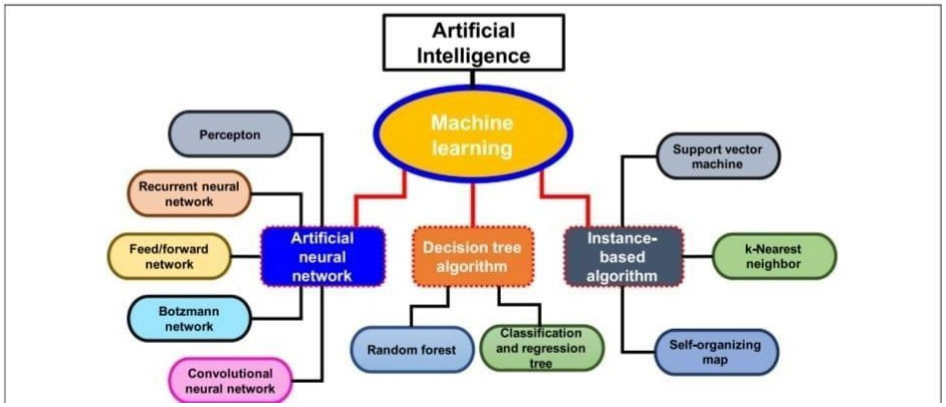


Fig.2

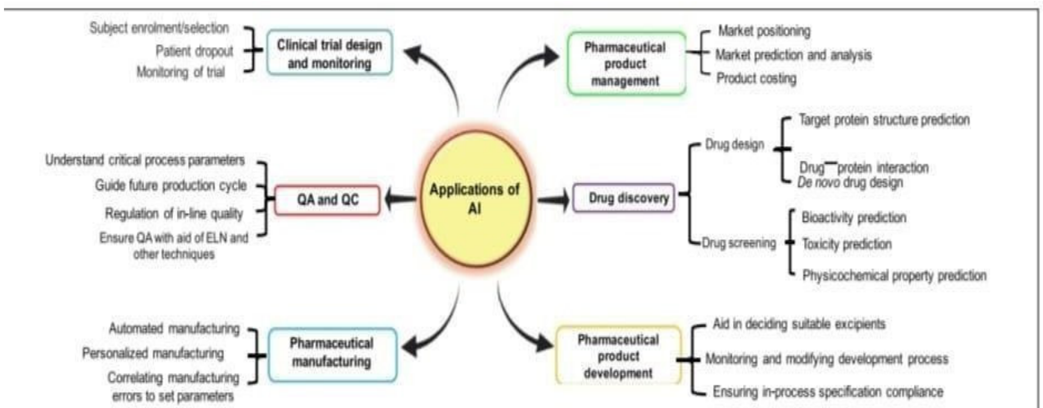


Fig.3 Applications of artificial intelligence (AI) in different subfields of the pharmaceutical industry , from drug discovery to pharmaceutical product management

AI IN DRUG DISCOVERY

The development of multiple pharmacological compounds is facilitated by the huge chemical space, which contains more than 1060 molecules (30) However, The medication development process is limited by the lack of sophisticated technologies, which makes it a costly and time-consuming operation that AI can help with (31) AI is able to identify hit and lead compounds, validate drug targets more quickly, and optimize drug structure design (32).

Despite its advantages, AI faces certain serious data chal- lenges, such as the magnitude, growth, diversity, and uncertainty of the data. The data sets accessible for drug development at pharmaceutical companies can comprise millions of molecules, and typical ML methods might lack the capacity to manage these forms of data .

Drug design techniques, such as cou- lomb matrices and molecular fingerprint recognition, examine the physical, chemical, and toxicological profiles to pick a lead compound (33) The desired chemical structure of a compound can be predicted using a variety of factors, including predictive models, molecular similarity, the process of molecule synthesis, and the use of in silico techniques (34).

Another strategy employed a multi objective automated replacement algorithm to optimize the potency profile of a cyclin-dependent kinase-2 inhibitor by examining its form similarity, biochemical activity, and physicochemical properties (35).

AI IN CLINICAL TRIAL DESIGN

Clinical trials, which take six to seven years and require a significant financial investment, are aimed to identifying the safety and effectiveness of a drug product in humans for a specific illness condition. However, the industry suffers a huge loss as just one in ten compounds that undergo these trials are successfully cleared (36).

The enrolment of patients occupies one-third of the clinical trial timeline. The success of a clinical trial can be secured by the finding appropriate patients, which would otherwise result in about 86% of instances of failure (37). AI can help choose just a certain sick

population for recruitment in Phase II and III of clinical trials by applying patient-specific genome–exposome profile analysis, which can help in early prediction of the available drug targets in the patients selected (38) ; (39).

Preclinical discovery of molecules as well as predicting lead compounds before the start of clinical trials by using other aspects of AI, such as predictive ML and other reasoning techniques, help in the early prediction of lead molecules that would pass clinical trials with consideration of the selected patient population [101].

By closely monitoring the patients and assisting them in adhering to the intended clinical trial protocol, this can be prevented [102]. Ai Cure created mobile software that tracked patients with schizophrenia's regular medication intake in a Phase II trial, increasing patient adherence by 25% and guaranteeing the clinical trial's successful conclusion [19].

AI IN PHARMACEUTICAL MANUFACTURE

Modern manufacturing systems are attempting to impart human knowledge to machines, constantly altering production practices due to the growing complexity of manufacturing processes and the growing demand for efficiency and higher-quality products [88].Similar systems, such as direct numerical simulations and large eddy simulations, incorporate advanced ways to handle compli- cated flow problems in manufacturing (40).

The estimated completion of granulation in granulators of capacities ranging from 25 to 600 l can be done efficiently using AI technology (41). The technology and neuro-fuzzy logic correlated important variables to their answers. In order to forecast the amount of granulation fluid to be supplied, the necessary speed, and the impeller diameter in both geometrically identical and dissimilar granulators, they developed a polynomial equation (42).

AI technologies called meta-classifiers and tablet-classifiers assist in controlling the final product's quality standards by pointing out potential manufacturing errors in tablets (43). A system that can use a processor that receives patient data to determine the most ideal combination of medication and dosing regimen for each patient and construct the desired transdermal patch appropriately has been the subject of a patent application (44).

Technological Advances in Miniaturization Consumer electronics have seen a significant transformation thanks to the ongoing advancements in shrinking technologies, which have allowed products to be designed in smaller formats , effective, and high-performing. Innovations in semiconductor technologies, microfabrication methods, and power-efficient designs are driving this advancement.

1. Power-Efficient Design: (45) emphasize how crucial power-efficient designs are for smaller consumer electronics. Innovations such as system-on-chip (SoC) technology and energy-efficient algorithms lower power usage while maintaining excellent performance. These developments are essential for portable electronics since they increase usability and battery life.
2. Advances in Semiconductor Technologies: (46) emphasizes the relevance of semiconductor technologies in miniaturization. Smaller and faster components can be achieved through technological innovations like FinFETs, multi-gate transistors, and improved lithography. These developments lay the groundwork for incorporating sophisticated features into small consumer electronics

3. Microfabrication Techniques: (47) talks on microfabrication methods such nanoscale patterning, thin-film deposition, and precision etching. These methods allow for the creation of incredibly tiny parts while maintaining performance and structural integrity. Applications include sensors, actuators, and MEMS, important for current consumer electronics.

Together, these technical developments propel miniaturization, resulting in consumer gadgets that are increasingly compact, effective, and multipurpose.

Table 1: Miniaturization technological advancements [9], [10], [11]

Innovation type	Key contributions	Percentage contribution
Power – Efficient Design	Reduced power consumption, Improved battery life	35%
Semiconductor Technologies	Smaller, faster, Efficient transistors	40%
Microfabrication Techniques	Ultra – small components with high perfomence	25%

MINIATURIZATION IN CONSUMER ELECTRONICS

As a result of progress in optical component design, packaging technologies, and artificial intelligence, consumer electronics have become much more miniature. These advancements make it possible to produce more compact, effective, and multipurpose gadgets that meet the demands of contemporary consumers.

1. ROLE OF AI AND MACHINE LEARNING:

(48) AI and machine learning play a crucial role in optimizing the design and manufacturing processes for miniaturized devices. In smaller devices , these approaches enhance the precision of component placement , lower design complexity, and boost energy efficiency. Additionally, AI helps with predictive modeling to assess dependability and performance, guaranteeing quality in small consumer devices.

2. ADVANCED PACKAGING TECHNOLOGIES:

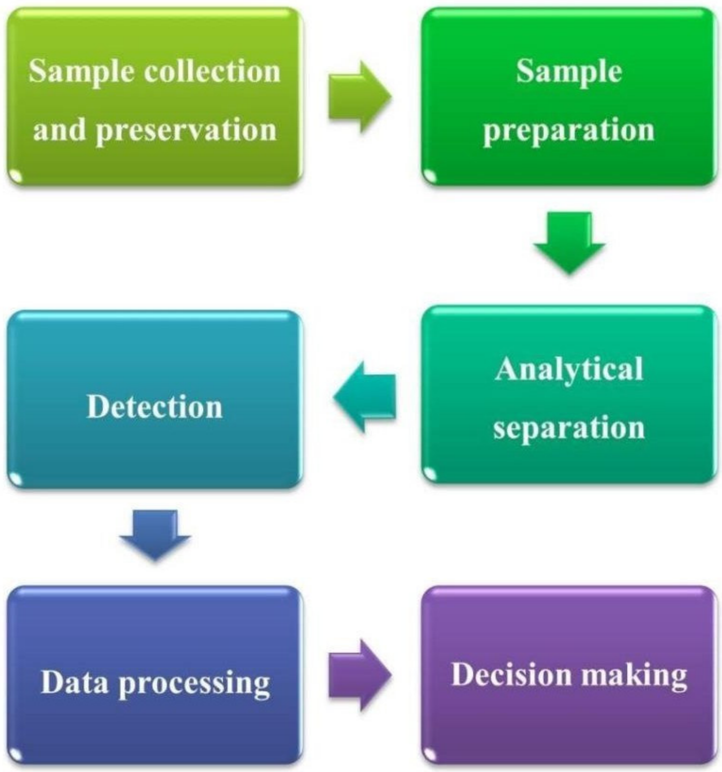
(49) highlight how crucial advanced packaging is for small electronics. Compact designs with high functionality and performance are made possible by technologies like chip-on-chip integration and system-in-package (SiP).

3. MINIATURIZATION OF OPTICAL COMPONENTS:

(50) discuss advancements in the miniaturization of optical components for consumer devices. High-performance optical systems in small form factors are made possible by methods like integrated photonics, compact waveguides, and micro-lens manufacturing. These innovations are critical for applications such as cameras, augmented reality devices, and advanced displays in consumer electronics.

All of the procedures required to extract analytical information from a sample—sample collection and preservation, sample preparation, separation, detection, data processing, and final decision—are included in the analytical process (Figure 3). These days, practically every stage of the analytical process has undergone downsizing.

However, the different steps of the analytical process have not been miniaturized to the same extent. For instance, sample collection and preservation is the step of the analytical process less subjected to the benefits of miniaturization, even though some autono mous and remote sensing analytical microsystems have been reported. Conversely, data acquisition and processing have achieved an excellent degree of miniaturiza tion.



Different steps of the analytical process

1. **Reduction of sample amount:**

The necessary sample volume required to carry out an appropriate analysis can be highly reduced by scaling down the sample preparation, separation and detection techniques. This is especially advantageous when dealing with scarce and/or precious samples.

2. **Decreased consumption of chemicals and solvents:**

A drastic decrease in the amount of analytical reagents and organic solvents that are needed can result from the miniaturization of any analytical process step. This is especially important in the case of analytical methods involving expensive and precious reagents such as enzymes and immunochemicals, as well as in the case of analytical meth odologies involving toxic reagents and/or organic solvents.

The miniaturization of separation techniques enables a significant reduction of mobile phase or electrolyte, as well as the amount of stationary phase materials.

3. Reduction of associated wastes:

As a result of the above mentioned advantages, the wastes generated along the whole analytical process can be highly reduced, thus resulting in more sustainable methodologies. Recycling and recovery of chemicals and organic solvents present in wastes, as well as the online genera tion of clean wastes are important tasks aiming to be adopted in analytical labo ratories (51)

4. **Improved sensitivity:**

Sensitivity of analytical methods can be increased through the utilization of a suitable miniaturized sample preparation technique and, in certain cases, by miniaturizing detection systems.

The improved design of recently developed analytical instrumentation can also yield increased sensitivity by using reduced sample volumes, although in several cases the sensitivity can be significantly deteriorated when the instru mentation is miniaturized. Advances in detection systems can minimize the loss of sensitivity.

5. **Rapidity:**

In analytical labs, time is a crucial factor. For this reason, the sample throughput plays a crucial role in technique development. The development of compact sample preparation, separation and detection devices can sig nificantly minimize the time needed to execute a single analysis. for example reduced usage of reagents and solvents, lower energy requirements and lesser amounts of trash.

6. **Portability:**

The downsizing of part or the whole of the analytical process steps contributes greatly to the mobility of analytical systems to the sampling location. Furthermore, portable analytical devices give timely and valuable information and limit the danger of sample decomposition and contamination during sample storage and trans portation.

7. **Power consumption:**

The reduction of analytical systems often requires a reduction of the power requirements. Because of this, smaller devices may run on batteries, which increases their portability.

MINIATURIZING DETECTION TECHNIQUES

The breakthroughs obtained in sectors such as electronics, engineering and material sciences have permitted the shrinking of analytical detection systems. The characteristic qualities of MEMS fabrication techniques, namely miniaturization, multiplicity and microelectronics, have enabled the batch manufacture of small sized detection systems (52). Miniaturization of analytical detection techniques requires the size reduction of different elements of conventionally-sized instruments without ignoring the performance of each component, in such a way that the overall miniaturized detection techniques yield comparable or improved analytical performance.

1. Molecular Spectrometry
2. Atomic Spectrometry
3. Mass Spectrometry
4. ElectroChemical Techniques

CONCLUSION :

The pharmaceutical and analytical industries are undergoing a profound transformation driven by the convergence of Artificial Intelligence (AI) and technological miniaturization. AI, encompassing Machine Learning and Deep Learning, acts as a vital tool for managing and leveraging the massive data generated by digitization. Its application extend across the entire product life cycle, from accelerating drug discovery and target validation to optimizing clinical trial design and ensuring quality control and customized dosing in manufacturing.

Concurrently, miniaturization, fueled by semiconductor breakthroughs and microfabrication, is revolutionizing analytical systems. This downscaling offers major advantages, including reduced sample and chemical consumption, minimal waste, improved sensitivity, and enhanced portability. While detection and data processing have achieved an excellent degree of miniaturization, nearly every step of the analytical process has benefited. Ultimately, the integration of these powerful AI capabilities and breakthrough miniaturized technologies paves the way for more efficient, precise, and sustainable procedures in drug development and analytical research.

REFERENCE:

1. M. Woschank, E. Rauch, H. Zsifkovits, A review of further directions for artificial intelligence, machine learning, and deep learning in smart logistics, Sustain- ability 12 (2020) 3760
2. S. Fahle, C. Prinz, B. Kuhlenkötter, Systematic review on machine learning (ML) methods for manufacturing processes–Identifying artificial intelligence (AI) methods for field application, Procedia CIRP 93 (2020) 413–418 .
3. D. Vrontis, M. Christofi, V. Pereira, S. Tarba, A. Makrides, E. Trichina, Artificial intelligence, robotics, advanced technologies and human resource management: a systematic review, Int. J. Human Res. Manag. 33 (2022) 1237–1266 . [4] J. Howard, Artificial intelligence: implications for the future of work, Am. J. Ind. Med. 62 (2019) 917–926
4. M. Soori, B. Arezoo, R. Dastres, Machine learning and artificial intelligence in CNC machine tools, a review, Sustain. Manuf. Service Econ. (2023) 100009
5. J. Howard, Artificial intelligence: implications for the future of work, Am. J. Ind. Med. 62 (2019) 917–926.
6. J.F. Arinez, Q. Chang, R.X. Gao, C. Xu, J. Zhang, Artificial intelligence in advanced manufacturing: current status and future outlook, J. Manuf. Sci. Eng. (2020) 142.
7. Abdel-Karim, B. M., Pfeuffer, N., & Hinz, O. (2021). Machine learning in information systems - a bibliographic review and open research issues. Electronic Markets, 31(3), 643– 670. https:// doi.org/10.1007/s12525-021-00459-2
8. Dunin-Barkowski, W. (2020). Editorial: Toward and beyond humanlevel AI. Frontiers in Neurorobotics, 14. https://doi.org/10. 3389/fnbot.2020.617446
9. Fukuda, T., Michelini, R., Potkonjak, V., Tzafestas, S., Valavanis, K., & Vukobratovic, M. (2001). How far away is “artificial man.” IEEE Robotics & Automation Magazine, 8(1), 66–73. https:// doi.org/10.1109/100
10. Arnott, D., & Pervan, G. (2005). A critical analysis of decision support systems research. Journalof Information Technology, 20(2), 67–87. https://doi.org/10.1057/palgrave.jit.2000035
11. Dellermann, D., Lipusch, N., Ebel, P., & Leimeister, J. M. (2019). Design principles for a hybrid intelligence decision support system for business model validation. Electronic Markets, 29(3), 423–441. https://doi.org/10.1007/s12525-018-0309-2
12. Ramesh, A. et al. (2004) Artificial intelligence in medicine. Ann. R. Coll. Surg. Engl. 86, 334–338
13. Miles, J. and Walker, A. (2006) The potential application of artificial intelligence in transport. IEE Proc.-Intell. Transport Syst. 153, 183–198
14. Yang, Y. and Siau, K. (2018) A Qualitative Research on Marketing and Sales in the Artificial Intelligence Age. MWAIS
15. Wirtz, B.W. et al. (2019) Artificial intelligence and the public sector—applications and challenges. Int. J. Public Adm. 42, 596–615
16. Rai, A., Constantinides, P., & Sarker, S. (2019). Next generation digital platforms: Toward human-AI hybrids. MIS Quarterly, 43(1), iii–ix.
17. Turing, A. M. (1950). Computing machine and intelligence. MIND, LIX(236), 433–460. https://doi.org/10.1093/2Fmind/2FLIX.236. 433
18. Rich, E., & Knight, K. (1991). Artificial intelligence. McGraw-Hill. Ritchie, S. G. (1990). A knowledge-based decision support architecture for advanced traffic management. Transportation Research Part A: General, 24(1), 27–37. https://doi.org/10.1016/0191- 2607(90) 90068-H
19. Poole, D. L., Mackworth, A., & Goebel, R. G. (1998). Computational intelligence and knowledge. Computational Intelligence: A Logical Approach, Ci, 1–22.
20. Russell, S. J., & Norvig, P. (2020). Artificial intelligence: A modern approach. In Artificial Intelligence (3rd ed.). https://doi.org/10. 1017/S0269888900007724
21. Collins, C., Dennehy, D., Conboy, K., & Mikalef, P. (2021). Artificial intelligence in information systems research: A systematic literature review and research agenda. International Journal of

Information Management, 60, 102383. https://doi.org/10. 1016/j.ijinfomgt.2021.102383
22. Copeland, M. (2016). What's the difference between artificial intelligence. Machine learning, and deep learning, 29. https://blogs. nvidia.com/blog/2016/07/29/whats- differenceartificial-intelligen ce-machine-learning-deep-learning-ai/. Accessed 3 May 2022.
23. Ongsulee, P. (2017). Artificial intelligence, machine learning and deep learning. 2017 15th International Conference on ICT and Knowledge Engineering (ICT\&KE), 1–6. https://doi.org/10. 1109/ICTKE.2017.8259629
24. Neisser, U. (1967). Cognitive psychology. Thinkingjudgement and Decision Makin. https://doi.org/10.1126/science.198.4319.816
25. Hastie, T., Tibshirani, R., & Friedman, J. (2017). The elements of statistical learning: Data mining, inference and prediction (Vol. 9). Springer
26. M. Woschank, E. Rauch, H. Zsifkovits, A review of further directions for artificial intelligence, machine learning, and deep learning in smart logistics, Sustainability 12 (2020) 3760.
27. Duch, W. et al. (2007) Artificial intelligence approaches for rational drug design and discovery. Curr. Pharm. Des. 13, 1497–1508
28. Blasik, A. et al. (2020) CURATE. AI: optimizing personalized medicine with artificial intelligence. SLAS Technol. 25, 95–105
29. Baronzio, G. et al. (2015) Overview of methods for overcoming hindrance to drug delivery to tumors, with special attention to tumor interstitial fluid. Front. Oncol. 5, 165
30. Mak, K.-K. and Pichika, M.R. (2019) Artificial intelligence in drug development: present status and future prospects. Drug Discovery Today 24, 773–780
31. Vyas, M. et al. (2018) Artificial intelligence:the beginning of a new era in pharmacy profession. Asian J. Pharm. 12, 72–76
32. Sellwood, M.A. et al. (2018) Artificial intelligence in drug discovery. Fut. Sci. 10, 2025– 2028
33. Chan, H.S. et al. (2019) Advancing drug discovery via artificial intelligence. Trends Pharmacol. Sci. 40 (8), 592–604
34. Brown, N. (2015) Silico Medicinal Chemistry: Computational Methods to Support Drug Design. Royal Society of Chemistry
35. Firth, N.C. et al. (2015) MOARF, an integrated workflow for multiobjective optimization: implementation, synthesis, and biological evaluation. J. Chem. Inf. Model. 55, 1169–1180
36. 100 Hay, M. et al. (2014) Clinical development success rates for investigational drugs. Nat. Biotechnol. 32, 40–51
37. 102 Fogel, D.B. (2018) Factors associated with clinical trials that fail and opportunities for improving the likelihood of success: a review. Contemp. Clin. Trials Commun. 11, 156– 164
38. Harrer, S. et al. (2019) Artificial intelligence for clinical trial design. Trends Pharmacol. Sci. 40, 577–591
39. Mak, K.-K. and Pichika, M.R. (2019) Artificial intelligence in drug development: present status and future prospects. Drug Discovery Today 24, 773–780
40. Rantanen, J. and Khinast, J. (2015) The future of pharmaceutical manufacturing sciences. J. Pharm. Sci. 104, 3612–3638
41. Faure, A. et al. (2001) Process control and scale-up of pharmaceutical wet granulation processes: a review. Eur. J. Pharm. Biopharm. 52, 269–277
42. Landin, M. (2017) Artificial intelligence tools for scaling up of high shear wet granulation process. J. Pharm. Sci. 106, 273–277
43. Gams, M. et al. (2014) Integrating artificial and human intelligence into tablet production process. AAPS PharmSciTech 15, 1447–1453
44. Kraft, D.L. System and methods for the production of personalized drug products. US20120041778A1.
45. A. V. Jones, P. F. Nguyen, and E. P. D. Brown, "Power-Efficient Design for Miniaturized Consumer Devices," IEEE Transactions on Very Large Scale Integration (VLSI) Systems, vol. 28, no 10, pp. 2253-2261, Oct. 2020, doi: 10.1109/TVLSI.2020.2997480.

46. J. W. Zhang, "The Role of Semiconductor Technologies in Advancing the Miniaturization of Consumer Electronics," IEEE Transactions on Semiconductor Manufacturing, vol. 33, no. 2, pp. 143-152, May 2020, doi: 10.1109/TSM.2020.2994310.
47. X. Y. Chen, Y. Z. Liu, and T. C. Wang, "Microfabrication Techniques for Miniaturizing Consumer Electronics," IEEE Transactions on Industrial Electronics, vol. 69, no. 7, pp. 45874593, Jul. 2022, doi: 10.1109/TIE.2022.3148490.
48. B. R. Singh and P. S. Patel, "AI and Machine Learning for Enhancing Miniaturization in Consumer Electronics," IEEE Transactions on Artificial Intelligence, vol. 3, no. 1, pp. 87-95, Jan. 2022, doi: 10.1109/TAI.2022.3170728.
49. C. K. Yang, J. Y. Lee, and W. Y. Hsu, "Advanced Packaging Technologies for Miniaturized Electronics," IEEE Transactions on Advanced Packaging, vol. 44, no. 3, pp. 198-205, May 2021, doi: 10.1109/TAP.2021.3079242.
50. J. H. Lin, T. J. Chan, and S. Y. Xu, "Miniaturization of Optical Components for Consumer Devices," IEEE Photonics Technology Letters, vol. 32, no. 5, pp. 408-416, Mar. 2020, doi: 10.1109/LPT.2020.2975309.
51. Garrigues, S., Armenta, S., & de la Guardia, M. (2010). Green strategies for decontamination of analytical wastes. TrAC Trends in Analytical Chemistry, 29, 592– 601.
52. Schuler, L. P., Milne, J. S., Dell, J. M., & Faraone, L. (2009). MEMS-based microspectrometer technologies for NIR and MIR wavelengths. Journal of Physics D: Applied Physics, 42, 133001.