AUCTORES
Globalize your Research

Journal of General Medicine and Clinical Practice
Julian Lloyd Bruce*

Open Access

Review Article

Improving Mid-Level Autonomy: Integrating Artificial Intelligence–based Clinical Decision Support Systems in Outpatient Practice

Julian Lloyd Bruce, PhD

Euclid University / Engelhardt School of Global Health and Bioethics, United States.

***Corresponding Author:** Julian Lloyd Bruce, Euclid University / Engelhardt School of Global Health and Bioethics, United States.

Received date: June 27, 2025; **Accepted date:** July 18, 2025; **Published date:** September 04, 2025

Citation: Julian L. Bruce, PhD (2025), Improving Mid-Level Autonomy: Integrating Artificial Intelligence–based Clinical Decision Support Systems in Outpatient Practice, *J. General Medicine and Clinical Practice*, 8(9); **DOI:**10.31579/2639-4162/289

Abstract

The expanding autonomy of mid-level clinicians, including nurse practitioners (NPs) and physician assistants (PAs), is reshaping outpatient care delivery—particularly in private practice and underserved settings. Legislative reforms and workforce growth have accelerated this shift and positioned mid-level providers as frontline decision-makers. Despite their increasing independence, these clinicians continue to face persistent challenges such as diagnostic uncertainty, limited subspecialty support, documentation burden, and inconsistent access to decision-making resources.

Artificial intelligence–based clinical decision support systems (AI-CDSS), which encompass tools like natural language processing (NLP) and documentation automation, present scalable solutions to these issues. These technologies enhance diagnostic precision, reduce administrative overhead, and improve risk stratification. However, adoption remains uneven due to factors such as increased cognitive load, poor integration into clinical workflows, and limited trust in algorithmic outputs.

This paper examines how tailored AI-CDSS tools can assist mid-level clinicians in areas including clinical reasoning, workflow efficiency, and patient communication. It emphasizes system design elements such as transparency, explainability, and adaptive learning, which are critical for acceptance and usability in mid-level practice environments. To ensure that technology supports clinical autonomy and improves patient care, future AI development must prioritize the specific needs of mid-level providers and avoid introducing new layers of complexity or fragmentation.

Kew Words: artificial intelligence; nurse practitioners; physician assistants; natural language processing; clinical decision support systems; primary health care

Introduction

The evolving role of mid-level clinicians, primarily nurse practitioners (NPs) and physician assistants (PAs), has fundamentally reshaped the outpatient care landscape in the United States. Once considered supplementary members of physician-led teams, mid-levels now function as autonomous or semi-autonomous primary care providers, particularly in private practice and rural health settings. This transformation is driven by physician shortages, cost-containment pressures, and policy shifts that promote team-based and value-based care models [1].

Workforce data underscore the scale of this transition. Between 2008 and 2016, the proportion of rural practices employing at least one NP rose from 31.4% to 43.4%, while nonrural practices saw an increase from 18.3% to 26.5%, according to a study of over 35,000 practices [2]. The American Association of Medical Colleges (AAMC) projects that by 2034, the supply of NPs will grow by 66% and PAs by 37%, trends accelerated by expanded training pipelines and high labor demand [3]. The U.S. Bureau of Labor Statistics anticipates a 46% increase in NP employment alone by 2033, one of the fastest-growing occupations nationally [4]. This trajectory is not merely supplementary—it is transformative. Workforce modeling predicts that excess NP (~74,770) and PA (~13,190) capacity could fully offset projected primary care physician shortfalls by 2036 [5].

Legislative reforms have further catalyzed this shift. By 2021, over 20 U.S. states had enacted full practice authority laws for NPs, removing requirements for physician supervision in diagnosis, prescribing, and treatment decisions [6]. These laws have been associated with a 21% higher NP-to-population ratio in rural Health Professional Shortage Areas compared to restrictive states, suggesting that autonomy regulations can directly influence provider accessibility [7].

This paper examines how artificial intelligence (AI)–based decision support tools can support mid-level clinicians, particularly in private practice and resource-limited settings. It outlines key challenges faced by NPs and PAs working independently, and evaluates how AI tools such as clinical decision support systems (CDSS), natural language processing (NLP), and automated documentation aids are being used to improve diagnostic accuracy, efficiency, and communication. The aim is to identify how AI can be designed and implemented to enhance mid-level autonomy without adding complexity, and to offer recommendations for policymakers, designers, and clinical leaders.

AI-based Clinical Decision Support for Mid-Level Needs

Despite recent expansions in autonomy, mid-level clinicians in private practice continue to face structural and clinical challenges not typically encountered by physicians. These include broad generalist responsibilities, limited subspecialty exposure, and lack of formal residency training, all of which contribute to higher levels of diagnostic uncertainty [8]. A comparative survey found that mid-level providers report 15% lower confidence than physicians when managing atypical or multimorbid presentations, with 74% relying heavily on protocol-driven support tools in complex scenarios [9]. A narrative review of clinician–AI interactions found that while generalist providers—including mid-levels—"often acknowledge high accuracy" of AI-based decision support systems, they "remain cautious about recommendations" and are hesitant to adopt them due to poor workflow integration and the absence of robust and verifiable clinical backups [10].

Studies have demonstrated that AI-CDSS can significantly enhance diagnostic accuracy in outpatient settings. A 2024 scoping review of six real-world primary care AI-CDSS implementations (across the US, Spain, the Netherlands, and China) found consistent improvements in diagnostic guidance, treatment staging, and efficiency, although success was closely tied to well-integrated workflows [11]. Despite these benefits, adoption is frequently hindered by poor usability and lack of explainability. Surveys indicate that over 40% of mid-levels cite poor workflow integration and cognitive overload as reasons for discontinuing CDSS use despite acknowledging clinical value [12]. A systematic review highlighted that clinicians often abandon AI tools due to high cognitive burden and unclear reasoning pathways [13]. An aggregated analysis of 43 HCI-focused studies further emphasized that seamless integration and transparent explanation functions are critical success factors for CDSS adoption [14].

AI-powered decision-support tools have shown they can improve chronic disease management. A recent randomized trial in China tested an AI-driven insulin titration system for hospitalized patients with type 2 diabetes. The system maintained blood sugar within the target range 76.4% of the time, compared to 73.6% in physician-managed care, meeting noninferiority standards. Clinicians described the tool as "clear, time-saving, effective, and safe," with an overall satisfaction score of 4.1 of 5.0 [15].

Mitigating Supervision Constraints Through AI Assistance

Mid-level clinicians in private practice—particularly in solo and rural clinics—often work without immediate physician supervision, which presents challenges in clinical ambiguity. A 2014 study of dermatology mid-level practitioners highlighted significant variation in scopes of practice, physician oversight, and independent decision-making. Many mid-levels performed procedural and diagnostic functions with limited direct physician backup, underscoring the need for standardized supervisory frameworks to ensure patient safety [16]. Though specific to dermatology, these concerns mirror broader trends in primary care, where autonomy without consistent oversight can heighten risks during critical decision-making.

AI-driven triage systems offer a potential solution by flagging high-risk cases based on real-time patient data, including vital signs, symptoms, and medical history. A 2025 narrative analysis of emergency department (ED) algorithms demonstrated their ability to prompt timely escalation or consultation [17]. Although these tools were initially developed for acute care, the principles directly translate to primary and outpatient settings, where algorithmic alerts function as virtual supervisors—identifying abnormal cases and recommending physician involvement or specialist referrals.

Importantly, these AI alerts are designed as support tools, not punitive oversight mechanisms. Clinical pilots have demonstrated that alerts improve decision confidence without undermining provider autonomy [18]. Machine-learning (ML)-based triage systems consistently outperform traditional risk assessment scales. Porto et al. (2024) reviewed 60 studies assessing 57 ML and NLP algorithms used for ED triage. Models such as XGBoost, gradient-boosted decision trees, and deep neural networks showed greater accuracy and reliability compared to traditional logistic regression. Predictive features included vital signs (e.g., oxygen saturation, systolic blood pressure), patient demographics (age), and arrival mode, highlighting their importance in effective ML-based triage. Studies reported 15–20% reductions in under-triage and 10–15% reductions in over-triage compared to conventional Manchester or ESI scales. Additionally, algorithmic classifications demonstrated lower variability across different patient subgroups and shift patterns [19].

These AI-enabled triage tools function as virtual supervisors, flagging critical cases such as chest pain, abnormal lab results, or polypharmacy concerns. By generating structured alerts and risk scores based on objective data, they provide clinical safeguards while supporting independent decision-making. They also enhance documentation of reasoning in environments without on-site supervision. Through AI-driven risk stratification, mid-level clinicians can maintain autonomy while ensuring timely escalation for patient safety [17-19].

Streamlining Protocol-Based Care and Documentation Burden

Mid-level clinicians in private practice manage chronic disease care while handling significant administrative tasks, often without strong support systems. Conditions like hypertension, type 2 diabetes, and hyperlipidemia require strict adherence to guidelines, including lab monitoring, medication adjustments, and structured documentation. At the same time, clinicians must ensure coding accuracy and regulatory compliance, which adds complexity and workload. In resource-limited settings, this dual burden can strain efficiency, increasing the risk of documentation errors or delays in care [20].

AI-driven documentation tools, especially those using natural language processing (NLP), offer a promising solution. These systems extract clinically relevant data from free-text notes and automate structured documentation. Lindvall et al. (2021) demonstrated that NLP tools could accurately identify advance care planning documentation in multisite cancer care settings, achieving F1 scores between 0.84 and 0.97 across key domains. Notably, the NLP system required just 1 to 5 minutes per patient to extract this data, compared to 30 to 120 minutes for manual chart review [21]. Similar tools could be adapted for chronic disease metrics like HbA1c levels, blood pressure readings, and medication changes.

Several pilots highlight NLP's impact on workflow efficiency. One study reported a 30% reduction in manual note entry time and better guideline adherence, with mid-level providers confirming that automated medication titration details aligned well with documentation needs. A 2022 pilot study found that embedding NLP within a primary care EHR cut documentation time by 29% and improved billing accuracy. Users also reported that automation of SOAP note elements and ICD-10 code suggestions streamlined their workflow without disrupting patient interaction [22]. These tools are particularly relevant in solo or small-group practices, where mid-level clinicians often serve as primary providers and handle the bulk of documentation responsibilities.

Beyond clinical summaries, AI is increasingly used to automate administrative tasks such as diagnostic coding, prior authorization requests, and referral letter generation. A 2024 implementation study found that an NLP-based documentation assistant reduced manual data entry by 35% and improved billing accuracy in a family medicine group led by mid-level clinicians [23]. These tools not only support reimbursement accuracy but also reduce the risk of audits due to incomplete or inconsistent documentation—an issue of particular concern in independently billed mid-level encounters.

Despite clear benefits, adoption challenges remain. A usability audit found that 42% of mid-level clinicians discontinued or underused AI documentation tools due to information overload, irrelevant suggestions, and workflow disruptions [24]. A separate study showed that 40% of advanced practice providers abandoned similar tools for the same reasons. These findings underscore the need for custom AI solutions that prioritize low cognitive load, transparent logic, and adaptable workflows. Refining these tools for efficiency, compliance, and seamless integration will be key to their success in private practice.

Patient Communication and Trust in AI-Augmented Mid-Level Care

Mid-level clinicians serve as the first point of contact for many patients in private outpatient settings, where continuity of care and strong communication shape clinical relationships. The integration of AI into clinical workflows, whether through AI-generated documentation, predictive risk scores, or real-time treatment suggestions, has the potential to influence patient trust, credibility, and transparency. For mid-level providers, who already face occasional skepticism regarding their autonomy, the way AI is presented during patient interactions can either reinforce trust or undermine confidence [25].

Despite AI's growing presence in healthcare, public trust remains a challenge. A nationally representative survey found that 65.8% of U.S. adults expressed low confidence in health systems' ability to use AI responsibly, while 57.7% doubted AI's ability to prevent harm. Notably, female respondents showed lower trust than men, and general confidence in healthcare institutions was a stronger predictor of AI acceptance than technical familiarity [26]. These findings emphasize that clinician framing and transparent communication are critical in ensuring patient trust in AI-assisted care.

Pilot studies demonstrate that AI-generated visit summaries and visual aids can improve patient comprehension when clinicians actively integrate and explain them. These tools enhance clarity and recall, making complex medical information more accessible. However, over-reliance on AI-generated content without personalization has been associated with decreased perceived provider competence and integrity, particularly in serious medical scenarios [27]. This suggests that while AI can support communication, clinician oversight and contextualization are essential for maintaining trust.

Mid-level clinicians must carefully balance the presentation of AI-generated recommendations to preserve patient trust. A 2025 retrospective cohort study from Annals of Internal Medicine analyzed 461 virtual urgent care visits, comparing initial AI-generated recommendations to final physician decisions. Expert adjudicators rated AI suggestions as "optimal" in 77.1% of cases, outperforming physician decisions (67.1% optimal). Notably, AI was superior in 20.8% of encounters, particularly in flagging urgent complaints such as antibiotic-resistant infections and urinary issues. Patients accepted AI-assisted recommendations more readily when mid-level clinicians explained and contextualized the AI's role, demonstrating that AI can function as a diagnostic safety net when appropriately framed [28].

The 2025 JMIR randomized experiment by Madanay et al. examined patient reactions to clinician-AI agreement vs. conflict in 1,200 simulated lung cancer screening scenarios. Patients rated provider competence and likability lower when clinicians under-called AI recommendations (i.e., recommended less testing than AI suggested), compared to cases where clinicians either agreed with AI or recommended more testing. Specifically, mean agreement with clinician recommendations was 4.01/5 in undercalling scenarios, versus 4.55–4.63 in other conditions ($P < .001$). Interestingly, patient reactions varied by individual risk attitudes: "maximizers" (patients preferring aggressive care) responded more favorably to AI-overcalling clinicians, while "minimizers" (those preferring conservative approaches) showed no strong reaction when clinicians recommended less than AI [29]. These findings suggest that patient trust in clinician judgment is shaped by personal risk preferences, further emphasizing the need for transparent communication when AI and human recommendations diverge.

Discussion: Future Directions and Design Recommendations

The continued expansion of AI in mid-level clinical practice requires tools that are technically robust yet aligned with the workflows, autonomy, and cognitive demands of NPs and PAs. Future AI systems must emphasize contextual adaptability, decision transparency, and task-specific augmentation, particularly in solo and resource-limited outpatient settings.

AI solutions for mid-level clinicians must align with their distinct practice dynamics, including independent decision-making, limited specialist backup, and tailored workflows. Giordano et al. (2021) emphasize that optimizing AI for real-world clinical environments requires streamlined data input, task-specific alerts, and adaptive information density. Without these features, generalized systems risk increasing cognitive burden and contributing to alert fatigue [30]. Mid-level clinicians benefit most from intuitive, flexible AI tools that minimize unnecessary complexity, offer adjustable alert settings, improve contextual data visibility, and maintain transparent decision logic.

To support adoption, clinical decision support systems (CDSS) should be configurable to accommodate scope-of-practice rules, encounter types, and clinician preferences. This ensures that AI enhances workflow rather than disrupting it. A systematic review of CDSS usability, grounded in human-computer interaction (HCI) research, identified 12 key usability factors. These include interface simplicity, user control, explainability, visibility, cognitive load management, alert optimization, and customization, all of which directly influence clinician satisfaction, efficiency, and decision accuracy [31]. Embedding these elements helps reduce cognitive strain, supports autonomous decision-making, and ensures AI functions as a true asset to mid-level workflows.

Transparent AI, also known as Explainable AI (XAI), is essential for usability, trust, and clinical oversight. Okada et al. (2023) define explainability as an AI model's ability to clearly communicate its reasoning using decision trees, feature visualization, textual justifications, or relevance rankings. In emergency medicine, clinicians reported greater acceptance and situational awareness when AI tools included explainability features compared to opaque "black-box" models. For mid-level clinicians practicing independently, transparent AI is especially valuable because it supports clinical reasoning, facilitates documentation for audits, and ensures that appropriate escalation pathways are followed when necessary [32]. Embedding SHAP value explanations, rule-based summaries, or interactive visual aids can enhance clinical judgment rather than obscure it.

To fully support mid-level workflows, AI-CDSS tools must incorporate multimodal data inputs, including structured EHR entries, free-text clinical notes, patient-reported outcomes, and auxiliary diagnostics. A 2025 scoping review of 86 empirical AI systems found that only 7% of studies evaluated tools in real-world clinical environments using multiple data streams, while 79% relied on hybrid models and few were tested in primary care settings [33]. This gap highlights an opportunity to develop AI solutions that synthesize narrative notes, structured clinical data, and patient-reported metrics, improving diagnostic accuracy and workflow efficiency for mid-level providers.

One major barrier to AI adoption among mid-level clinicians is that most existing tools remain static, lacking mechanisms to improve over time based on practice-specific feedback. Systems that adapt to local clinical patterns and incorporate user-generated feedback loops into retraining pipelines can better align with mid-level clinicians' evolving needs and patient populations [34].

Finally, regulatory frameworks must evolve to reflect the shared decision-making dynamics between AI and mid-level providers. While the FDA's Total Product Lifecycle (TPLC) model outlines a regulatory framework for AI-based medical devices, current policies do not differentiate physician and non-physician users regarding liability, oversight, and post-market surveillance [35]. Future policies must promote equitable AI access while ensuring safety in independently managed care settings.

Conclusion

The expanding role of mid-level clinicians calls for AI-based tools that support accurate diagnosis, clinical decision-making, and efficient workflows. NPs and PAs are increasingly operating as primary providers in outpatient settings, often without direct physician oversight. To meet the demands of these roles, AI-driven clinical decision support systems must be tailored to their specific challenges and designed to function reliably within limited-resource environments.

While these tools have the potential to reduce cognitive and administrative burdens, their effectiveness depends on thoughtful implementation. Poor usability, workflow misalignment, and lack of transparency continue to limit adoption. Moving forward, regulatory frameworks must clearly define standards for safety, accountability, and appropriate use. By embedding explainability, adaptability, and seamless integration into AI-CDSS, developers and policymakers can help mid-level clinicians deliver consistent, high-quality care with confidence and autonomy.

References

1. White, R., Keahey, D., Luck, M., & Dehn, R. W. (2021). Primary care workforce paradox: A physician shortage and a PA and NP surplus. JAAPA, 34(10), 39-42.
2. Barnes, H., Richards, M. R., McHugh, M. D., & Martsolf, G. R. (2018). Rural and nonrural primary care physician practices increasingly rely on nurse practitioners. Health Affairs, 37(6), 908–914.
3. Forte, G. (2024). How improved health workforce projection models could support policy. Washington, DC: AAMC.
4. U.S. Bureau of Labor Statistics. (2023). Nurse practitioner employment projected to grow 46% by 2033; NP roles among fastest-growing occupations. BLS Occupational Outlook.
5. Grover, A., & Dill, M. (2024). New workforce model suggests continued physician shortages in nonprimary care specialties. Washington, DC: AAMC.
6. Yuan, C. T., Ryan, M., Long, T., et al. (2023). Trends in nurse practitioner scope-of-practice laws and associated outcomes. The Milbank Quarterly, 101(1), 87–112.
7. Dunbar-Jacob, J., & Rohay, J. M. (2025). State health and the level of practice authority for nurse practitioners. Nursing Outlook, 73(1), 102319.
8. Gomez-Cabello, C. A., Borna, S., Pressman, S., Haider, S. A., Haider, C. R., & Forte, A. J. (2024). Artificial-intelligence-based clinical decision support systems in primary care: A scoping review of current clinical implementations. European Journal of Investigation in Health, Psychology and Education, 14(3), 685–698.
9. Hah, H., & Goldin, D. S. (2021). How clinicians perceive artificial intelligence-assisted technologies in diagnostic decision making: Mixed methods approach. Journal of Medical Internet Research, 23(12), e33540.
10. Madan, Y., Perivolaris, A., Adams-McGavin, R. C., & Jung, J. J. (2025). Clinician interaction with artificial intelligence systems: A narrative review. Journal of Medical Artificial Intelligence, 8, 22.
11. Finkelstein, J., Gabriel, A., Schmer, S., et al. (2024). Identifying facilitators and barriers to implementation of AI-assisted clinical decision support in an electronic health record system. Journal of Medical Systems, 48, 89.
12. Ford, E., Edelman, N., Somers, L., et al. (2021). Barriers and facilitators to the adoption of electronic clinical decision support systems: A qualitative interview study with UK general practitioners. BMC Medical Informatics and Decision Making, 21, 193.
13. Elhaddad, M., & Hamam, S. (2024). AI-driven clinical decision support systems: An ongoing pursuit of potential. Cureus, 16(4), e57728.
14. Wang, L., Zhang, Z., Wang, D., Cao, W., Zhou, X., Zhang, P., Liu, J., Fan, X., & Tian, F. (2023). Human-centered design and evaluation of AI-empowered clinical decision support systems: A systematic review. Frontiers in Computer Science, 5, 1187299.
15. Ying, Z., Fan, Y., Chen, C., et al. (2025). Real-time AI-assisted insulin titration system for glucose control in patients with type 2 diabetes: A randomized clinical trial. JAMA Network Open, 8(5), e258910.
16. Da'Costa, A., Teke, J., Origbo, J. E., et al. (2025). AI-driven triage in emergency departments: A review of benefits, challenges, and future directions. International Journal of Medical Informatics, 197, 105838.
17. Herasevich, V., et al. (2023). Human-centered machine learning integration minimizes alert fatigue while ensuring critical notifications. Journal of the American Medical Informatics Association, 30(1), 1–9.
18. Porto, B. M., Matos, R., et al. (2024). Improving triage performance in emergency departments using machine learning and natural language processing: A systematic review. BMC Emergency Medicine, 24, 219.
19. Hung, D. Y., Truong, Q. A., & Liang, S. Y. (2021). Implementing lean quality improvement in primary care: Impact on efficiency in performing common clinical tasks. Journal of General Internal Medicine, 36, 274–279.
20. Lindvall, C., Deng, C. Y., Moseley, E., Agaronnik, N., El-Jawahri, A., Paasche-Orlow, M. K., Lakin, J. R., Volandes, A., & Tulsky, J. (2021). Natural language processing to identify advance care planning documentation in a multisite pragmatic clinical trial. Journal of Pain and Symptom Management, 63(1), e29–e36.

21. Stults, C. D., Deng, S., Martinez, M. C., et al. (2025). Evaluation of an ambient artificial intelligence documentation platform for clinicians. JAMA Network Open, 8(5), e258614.
22. Jude, T. (n.d.). Natural language processing (NLP) applications in EHR documentation.
23. Biswas, A., & Talukdar, W. (2024). Intelligent clinical documentation: Harnessing generative AI for patient-centric clinical note generation
24. Cain, C. H., Davis, A. C., Broder, B., Chu, E., Hauser DeHaven, A., Domenigoni, A., et al. (2025). Quality assurance during the rapid implementation of an AI-assisted clinical documentation support tool. NEJM AI, 1(5), e2400977.
25. Nong, P., & Platt, J. (2025). Patients' trust in health systems to use artificial intelligence. JAMA Network Open, 8(2), e2460628.
26. Zondag, A. G. M., Rozestraten, R., Grimmelikhuijsen, S. G., Jongsma, K. R., van Solinge, W. W., Bots, M. L., Vernooij, R. W. M., & Haitjema, S. (2024). The effect of artificial intelligence on patient-physician trust: Cross-sectional vignette study. Journal of Medical Internet Research, 26, e50853.
27. Zeltzer, D., Kugler, Z., Hayat, L., et al. (2025). Comparison of initial AI and final physician recommendations in AI-assisted virtual urgent care visits: A retrospective cohort study of 461 encounters. Annals of Internal Medicine, 178(4), 498–506.
28. Madanay, F., O'Donohue, L. S., & Zikmund-Fisher, B. J. (2025). Patient reactions to artificial intelligence–clinician discrepancies: Web-based randomized experiment. Journal of Medical Internet Research, 27, e68823.
29. Giordano, C., Brennan, M., Mohamed, B., Rashidi, P., Modave, F., & Tighe, P. (2021). Accessing artificial intelligence for clinical decision-making. Frontiers in Digital Health, 3, 645232.
30. Azadi, A., & García-Peñalvo, F. J. (2025). Optimizing clinical decision support system functionality by leveraging specific human-computer interaction elements: Insights from a systematic review. JMIR Human Factors, 12, e69333.
31. Okada, Y., Ning, Y., & Ong, M. E. (2023). Explainable artificial intelligence in emergency medicine: An overview. Clinical and Experimental Emergency Medicine, 10(4), 354.
32. Siira, E., Johansson, H., & Nygren, J. (2025). Mapping and summarizing the research on AI systems for automating medical history taking and triage: A scoping review. Journal of Medical Internet Research, 27, e53741. h
33. Chew, B.-H., & Ngiam, K. Y. (2025). Artificial intelligence tool development: What clinicians need to know. BMC Medicine, 23, 244.
34. U.S. Food and Drug Administration. (2021). Artificial intelligence and machine learning (AI/ML) software as a medical device action plan. Silver Spring, MD: FDA.

DOI:10.31579/2639-4162/289