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Artificial Intelligence Across Engineering Disciplines

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Abstract
This narrative review examines how artificial intelligence is reshaping Electrical and Electronic, Mechanical and Biomedical Engineering, with particular attention to healthcare systems in Botswana. It compares current applications, workforce skills, implementation barriers and governance risks, arguing for gradual, secure, locally validated adoption supported by reliable infrastructure and accountable human oversight.

Keywords: Artificial intelligence; Engineering; Biomedical engineering; Digital health; Botswana; Responsible AI

1. Introduction

Artificial intelligence (AI) is now part of routine engineering practice rather than a technology confined to research laboratories. Engineers use machine learning to recognise patterns, predict system behaviour, optimise processes and automate selected tasks. In mechanical systems, AI supports predictive maintenance; in civil engineering, computer vision assists structural inspection; and in design, generative methods help engineers explore possible solutions more quickly [1-3]. These tools extend an engineer's ability to analyse complex data, but they do not remove professional responsibility. Their performance still depends on reliable data, careful validation and safe deployment. AI is therefore most useful as an aid to engineering judgement, especially where its recommendations can be checked against physical evidence and professional knowledge.

Electrical and Electronic Engineering, Mechanical Engineering and Biomedical Engineering use many of the same AI methods, but for different purposes [4]. Electrical engineers apply them to power forecasting, energy management and fault detection. Mechanical engineers use them in maintenance, manufacturing inspection and design optimisation. Biomedical engineers apply them to medical imaging, intelligent devices and prosthetic control. In each field, data are collected from a physical or digital system, processed by an algorithm and translated into information that can support a decision. However, the meaning of that information and the consequences of error differ across disciplines. This review therefore compares the three fields while recognising that every AI application must meet the technical, safety and ethical demands of its own working environment.

Healthcare is also an engineering environment because patient care depends on medical devices, electronic records, diagnostic systems, wearable technologies and hospital infrastructure. AI can help turn these devices and records into practical decision-support tools. It may assist image analysis, monitor changes in vital signs, support adaptive medical devices and identify equipment that is likely to fail. At system level, it can help organise clinical information and improve planning. However, a technically accurate model is not automatically useful in practice. It must fit clinical workflows, protect patient information and provide information that healthcare professionals can interpret and act upon. Engineers, data specialists and

clinicians must therefore work together so that technical performance is matched by clinical relevance, patient safety and clear professional responsibility [5].

Across Africa, interest in AI and digital health is increasing, but adoption remains uneven. Common barriers include limited infrastructure, shortages of trained staff, restricted funding and a lack of representative local data [6,7]. Botswana is a useful setting for examining these opportunities and constraints. A study of the VisualDx clinical decision-support system in Botswana found potential benefits for clinical decision-making, while also identifying slow connectivity, data-protection requirements, image quality, staff training, regulation and sustainable funding as practical challenges [5]. The lesson is straightforward: useful software alone is not enough. Successful implementation also depends on reliable infrastructure, sound governance, workforce capacity and long-term technical support. Claims about AI in Botswana should therefore distinguish clearly between existing evidence, pilot experience and proposed future applications.

This narrative review examines AI applications in Electrical and Electronic Engineering, Mechanical Engineering and Biomedical Engineering. It considers intelligent systems, predictive maintenance, design, robotics, medical devices and digital healthcare, together with emerging careers and required skills. Particular attention is given to healthcare opportunities and barriers in Botswana, including infrastructure, data quality, workforce readiness, privacy, safety and sustainable implementation. The following sections explain the review method, compare applications across the three disciplines, discuss Botswana's healthcare context and consider the professional, ethical and governance requirements for responsible adoption.

2. Review Methodology

This study adopted a narrative literature review, a flexible qualitative approach used to identify, analyse and synthesise published literature without the rigid protocol of a systematic review. Narrative reviews are appropriate when a topic requires conceptual synthesis across varied forms of evidence rather than exhaustive statistical comparison [8,9]. This approach was selected because the subject crosses Electrical and Electronic Engineering, Mechanical Engineering, Biomedical Engineering, healthcare technology and workforce-development literature. It allowed engineering applications, clinical implications, professional skills and regional implementation challenges to be organised into connected themes. The review is not presented as a systematic review because no formal systematic-review protocol or meta-analysis was undertaken.

Literature searches were conducted on 25 August 2026 using Google Scholar, with relevant records verified through PubMed, IEEE Xplore, journal publishers and official institutional websites. Search phrases combined terms such as 'artificial intelligence', 'machine learning', 'electrical engineering', 'mechanical engineering', 'biomedical engineering', 'healthcare', 'workforce skills', 'Africa' and 'Botswana', using AND or OR where appropriate. The main publication range was 2015-2026, although older foundational review-method papers were retained when directly relevant. Peer-reviewed research articles, narrative and systematic review papers, conference literature and verified government or institutional documents were considered. Titles, abstracts and available full texts were screened for relevance, while reference lists and 'Cited by' links were used for citation chaining [9,10]. No fixed source total is reported because the review was thematic rather than exhaustive.

Sources were selected according to their relevance to AI applications, credibility, clear engineering connection and value to healthcare systems or workforce development. Priority was given to peer-

reviewed studies, established review papers and verified institutional documents; commercial webpages were used only for practical examples when stronger academic evidence was unavailable. Contrasting findings and implementation barriers were considered to reduce selective interpretation. Nevertheless, narrative reviews remain more dependent on author judgement and are less reproducible than systematic reviews [8,11]. Google Scholar also has inconsistent coverage and limited transparency in ranking and indexing, so relevant regional studies may have been missed [10]. Botswana-specific research on engineering applications of AI remains limited; consequently, some conclusions draw cautiously on wider African evidence and should not be interpreted as proof of national implementation.

3. AI in Electrical and Electronic Engineering

Artificial intelligence is transforming modern power grids by improving demand forecasting, fault detection, renewable-energy integration and real-time load balancing. Smart meters and advanced metering infrastructure collect detailed consumption data, while machine-learning algorithms combine historical demand with weather and operating conditions to estimate peak electricity use. These forecasts help grid operators balance supply and demand, schedule generation and manage battery charging or discharge more efficiently. Sensor networks on transmission lines and substations can also identify abnormal voltage, current or equipment behaviour, allowing faults to be located earlier and maintenance to be planned before wider disruption occurs. AI models can further forecast variable solar and wind output, helping operators integrate renewable energy without weakening grid stability [12]. These capabilities can improve reliability, resilience and operational efficiency, although they depend on accurate data, secure communications and dependable infrastructure. In Botswana, they should presently be viewed as potential applications rather than evidence of a confirmed national AI-enabled smart-grid programme.

Artificial intelligence, the Internet of Things and edge computing connect sensors with local data processing for industrial and hospital monitoring. In hospitals, connected devices can track heart rate, oxygen saturation and equipment location, while industrial sensors monitor vibration, temperature and operating conditions. Edge computing processes selected data close to the device instead of sending every reading to a distant cloud platform. This reduces latency and allows immediate alerts when a patient's condition changes or machinery shows signs of failure, even when connectivity is slow or intermittent [13]. Local processing can also limit unnecessary transmission of sensitive information, but it does not remove privacy or cybersecurity risks. Connected monitors, pumps and gateways remain vulnerable to unauthorised access, manipulation and service disruption. Engineers must therefore apply authentication, encryption, software updates and network isolation. Edge systems also require reliable power, adequate computing capacity and maintenance; otherwise, limited connectivity and device resources can weaken real-time performance.

4. AI in Mechanical Engineering

Predictive maintenance combines continuous condition monitoring with machine learning to estimate when equipment is deteriorating and when intervention is actually needed. Sensors record vibration, temperature, pressure and sound because changes in these signals can reveal imbalance, misalignment, bearing wear, leakage or abnormal friction. Algorithms compare current measurements with historical operating patterns, detect anomalies and may estimate the remaining useful life of a component [14]. This differs from preventive maintenance, which services equipment at fixed calendar or operating-hour intervals whether deterioration is present or not. Predictive maintenance is therefore data-driven, whereas

preventive maintenance is schedule-driven. When implemented carefully, it can reduce unplanned downtime, prevent secondary damage, improve worker safety and avoid unnecessary replacement of healthy parts. However, predictions are only as reliable as the sensors, maintenance records and operating data used. Engineers must still inspect equipment, interpret alerts and decide whether a machine can continue operating safely or should be stopped for repair.

Artificial intelligence is shifting mechanical design and manufacturing towards a more connected, iterative and data-driven process. In generative design, engineers define boundary loads, weight targets, stress limits, materials and manufacturing constraints, after which algorithms explore many possible geometries. Computer-aided engineering tools can then simulate performance and help narrow the design space before physical prototypes are produced. In manufacturing, robots use sensor data to support adaptive assembly, machine tending and variable pick-and-place tasks, while computer-vision systems inspect surfaces, dimensions and component alignment for defects [15,16]. Vision data can also connect quality problems to tool wear or process variation, allowing production teams to intervene before large quantities of scrap are created. These systems do not remove professional responsibility. Engineers must verify that generated designs satisfy safety requirements, test assumptions and prototypes, evaluate cost and manufacturability, and consider whether components can be maintained and repaired. A design that is mathematically optimised may still be unsuitable if it is unsafe, too expensive or impractical to manufacture.

5. AI in Biomedical Engineering

Artificial intelligence supports medical imaging by classifying images, segmenting anatomical structures and highlighting areas that may require closer examination. Deep-learning models can process radiographs, computed-tomography scans, magnetic-resonance images and retinal images to detect patterns associated with abnormalities. In practice, these systems should support radiologists by prioritising cases, marking suspicious regions or providing a second assessment; they should not be described as independently diagnosing patients. Clinical usefulness depends on external validation across different hospitals, patient groups, scanners and image-acquisition procedures. Reviews show that model performance often falls when an algorithm is tested on data from institutions outside its development setting [17]. Dataset bias is therefore a serious engineering and clinical concern. If training images underrepresent particular populations, diseases or equipment types, predictions may not generalise safely. Responsible deployment requires representative datasets, transparent performance reporting, clinician oversight and continued monitoring after implementation. Final diagnostic and treatment decisions remain with qualified healthcare professionals.

Artificial intelligence and machine learning are extending the capabilities of medical robots and intelligent devices. Robot-assisted surgical systems can stabilise instruments, filter hand tremor and support precise movement, while computer vision may help track tools and anatomical structures during a procedure. Rehabilitation robots and exoskeletons can adjust assistance according to a patient's movement and progress. Intelligent prosthetic devices use signals from muscles, nerves or other sensors to interpret intended movement and adapt control to changing tasks. Monitoring equipment can likewise identify abnormal readings and issue alerts for clinical review [18,19]. These technologies remain tools under human control rather than independent caregivers. Safety depends on clinical validation, risk assessment, secure software, calibration, preventive maintenance and clear procedures for responding to faults. Surgeons, therapists, biomedical engineers and healthcare institutions retain professional accountability for how devices are selected, configured and used. Automation may improve precision and

personalisation, but it cannot replace informed consent, clinical judgement or responsibility for patient outcomes.

AI-enabled wearables and remote-monitoring systems can collect heart rate, activity, sleep, blood pressure, oxygen saturation, temperature and other physiological measurements outside traditional clinical settings. Machine-learning models can analyse repeated readings to identify unusual patterns, support chronic-condition management and generate early-warning alerts. For people living with cardiovascular disease, diabetes or respiratory conditions, continuous monitoring may help clinicians observe trends between visits and support telemedicine consultations. Wearables may also encourage self-monitoring, physical activity and adherence by giving users timely feedback [20]. However, consumer and medical devices differ in accuracy, and readings can be affected by sensor placement, movement, skin characteristics, battery level and missing data. An alert is not useful unless responsibility for reviewing and acting on it is clearly assigned. Health services must define escalation pathways, response times and documentation requirements so that warnings are not ignored or assumed to be automatically managed. Reliable use also requires informed consent, secure data transfer, interoperability with health records and clinical validation in the population being monitored.

6. AI and Healthcare Systems in Botswana

Botswana's healthcare system is organised as a referral network linking community-based primary care with specialised hospital services. Mobile stops and health posts provide limited services, while clinics deliver primary healthcare, outpatient treatment, preventive care and referrals. Clinics with maternity services provide a broader package of care. Primary hospitals manage common diseases, injuries and immediate health threats; district hospitals provide greater inpatient, diagnostic, surgical and longer-term capacity; and referral hospitals deliver specialised services [21]. In April 2025, responsibility for clinics, health posts, mobile stops and their staff was transferred to district councils under the Ministry of Local Government and Traditional Affairs, while primary, district and referral hospitals remained under the Ministry of Health [22]. This layered structure is important when considering digital health because information and referrals must move between facilities with different staffing, equipment and connectivity. It means that any AI application would need to fit established referral pathways rather than operate as an isolated technological project.

Botswana's existing health-information systems provide an important foundation for future AI, although the available data remain distributed across different platforms. Published evidence identifies the Patient Information Management System (PIMS) and Integrated Patient Management System (IPMS) as systems used to collect and store patient and service information in public healthcare. PIMS has operated as a decentralised system in health facilities, while IPMS supports clinical and operational information in larger facilities. Botswana has also used DHIS2 for health reporting and malaria case-based surveillance [23,24]. The National eHealth Strategy 2020-2024 recognised information and communication technologies as tools for strengthening healthcare delivery [25]. These platforms can supply historical and operational data for forecasting, quality monitoring and decision support. However, AI requires more than the existence of electronic records. Data must be complete, consistently coded, interoperable and legally accessible for an approved purpose. Fragmented records, delayed reporting and incompatible identifiers must therefore be addressed before reliable models can be developed or deployed.

In Botswana, artificial intelligence offers several realistic healthcare opportunities, but these should be treated as proposals rather than confirmed national programmes. Historical attendance, disease and

seasonal data could support forecasts of patient demand, helping facilities plan staffing, beds and clinic schedules. Pharmacy and procurement data could improve stock planning by identifying likely medicine shortages, unusual consumption or products approaching expiry. Clinical teams could use risk models to prioritise follow-up for patients who miss appointments or show signs of deterioration, provided that decisions remain under professional oversight. In referral facilities, validated imaging tools could highlight suspicious areas for radiologists, while equipment data could support predictive maintenance of oxygen systems, laboratory analysers and imaging units. AI-assisted remote consultation could also help frontline workers obtain specialist guidance for rural patients, building on Botswana's documented interest in telemedicine [26]. Each application would require local validation, clear accountability, secure access and integration with existing systems. The immediate priority is therefore to strengthen data quality and workflows before attempting large-scale automation.

Adopting artificial intelligence in Botswana's healthcare system would require more than purchasing software. Inconsistent or incomplete records can produce unreliable models, and AI cannot correct poor data merely by being added to an existing system. Fragmented platforms, limited interoperability and delayed reporting reduce the quality of information available for training and operational decisions [23,27]. Connectivity interruptions, unreliable power, ageing equipment and weak maintenance capacity may prevent cloud-based or connected tools from operating consistently. Costs extend beyond procurement to licences, secure infrastructure, calibration, updates, technical support and staff training. Cybersecurity and privacy are equally important because health information is sensitive and connected devices create additional points of attack. Hospitals also need engineers, data specialists and clinicians who can evaluate model performance, recognise bias and investigate failures. Staff may resist systems that are difficult to use, poorly explained or imposed without consultation. Successful adoption therefore depends on workflow integration, clinical leadership, user training and clearly assigned responsibility for alerts and decisions. Without these foundations, AI may add complexity and risk rather than improve patient care.

7. Career Opportunities and Required Skills

The growth of artificial intelligence is creating and reshaping careers that combine computing with specialised engineering or healthcare knowledge. AI engineers design, train and deploy machine-learning systems, while data scientists organise and interpret large datasets for prediction and decision support. Robotics engineers integrate algorithms with sensors, control systems and mechanical hardware. IoT systems engineers connect devices, communication networks and edge-computing platforms. In healthcare, clinical engineers manage medical technologies and evaluate their safety within hospital environments, whereas health-informatics specialists connect electronic records, data standards and clinical workflows. AI validation specialists test performance, bias, reliability and regulatory compliance before and after deployment. None of these roles depends on software knowledge alone. Effective practice requires engineering fundamentals, statistics and data skills together with knowledge of the relevant physical, industrial or clinical environment. African health-informatics research particularly emphasises combining technical competence with healthcare-domain knowledge and an understanding of local workflows [28,29].

Engineers working with artificial intelligence need both technical competence and sound human judgement. Programming in Python, MATLAB or similar tools supports data analysis, modelling and algorithm development, while knowledge of machine learning helps engineers select, train and evaluate

appropriate models. Work involving physical systems also requires understanding of sensors, signal processing, control, electronics and core engineering principles. Systems-integration skills are needed to connect software, databases, devices and existing infrastructure, and cybersecurity knowledge is essential for protecting connected systems and sensitive information. Technical ability alone is insufficient. Engineers must communicate model limitations clearly, collaborate with clinicians, technicians, managers and users, and apply critical thinking when outputs conflict with physical evidence or professional experience. Ethical judgement is required to identify bias, protect privacy, maintain human oversight and decide when automation should not be used. Contemporary competency frameworks therefore combine programming, analytics and system design with teamwork, communication, adaptability, human-centred thinking and responsible AI practice [30,31]. These skills must be updated continuously as technologies, standards and risks change.

8. Ethical, Safety and Governance Challenges

Healthcare AI depends on sensitive patient information from clinical records, images and connected devices. These data require secure storage, encryption, role-based access controls, audit logs and clear limits on authorised use. Patients should receive understandable information and provide informed consent where required, particularly when data may be reused to train or evaluate algorithms [32]. Cybersecurity is also a patient-safety issue: attacks on networked monitors, pumps or imaging systems can expose records, interrupt services or alter device behaviour. Security must therefore be maintained throughout the system and device lifecycle through risk assessment, updates, vulnerability monitoring and incident-response plans [33]. Privacy cannot be treated as separate from usefulness. A technically effective system may still fail if people fear surveillance, unauthorised disclosure or misuse of their information. One serious privacy breach can undermine patient and staff trust, reducing willingness to use an otherwise beneficial digital-health service.

Algorithmic bias occurs when an AI system produces systematically unequal results across populations. In healthcare, this may arise from poor-quality labels, missing records or training data that underrepresent African patients, diseases, skin tones, equipment and clinical environments. Even neutral-looking variables can reproduce inequality; for example, healthcare expenditure may be a misleading substitute for illness when some groups historically receive less care [34]. A model developed mainly from North American, European or Asian data may therefore perform differently in Botswana. High accuracy does not prove that performance is fair across age, sex, location or population groups. Before clinical deployment, models should be tested using local data, equipment and workflows, with results reported by subgroup. Validation should continue after implementation because populations, clinical practices and data quality change over time. Where fair performance cannot be demonstrated, deployment should be limited, redesigned or rejected [35].

When an AI recommendation is wrong, responsibility cannot be placed on the algorithm itself. Developers and engineers are responsible for design, data quality, testing, cybersecurity and documented limitations. Healthcare professionals must verify that inputs are accurate, interpret outputs within the patient's clinical context and exercise independent judgement before acting. Institutions oversee procurement, validation, training, workflows, monitoring and failure reporting [36]. Regulators and approving bodies establish minimum requirements, but compliance does not remove the duties of developers, clinicians or hospitals. High-risk diagnostic and treatment decisions therefore require human oversight, authority to override the system and an auditable record of the information used. Explainability should provide clinicians with

enough information to identify uncertainty and inappropriate recommendations; it should not be treated as proof that a model is safe. Accountability requires named decision-makers, continuing performance review and practical routes for patients to question decisions and seek redress [37].

9. Discussion and Professional Reflection

Electrical and Electronic Engineering, Mechanical Engineering and Biomedical Engineering apply AI to different problems, but their underlying structure is closely related. Electrical systems use measurements from meters, networks and power equipment to forecast demand and identify faults. Mechanical systems use vibration, temperature, pressure, sound and images to predict deterioration or inspect manufacturing quality. Biomedical systems use physiological signals, medical images and device data to support monitoring, rehabilitation and clinical assessment. Across all three disciplines, sensors convert physical conditions into data, algorithms identify patterns or predict future behaviour, and outputs assist professional decisions. The main difference lies in the consequence of error and the domain knowledge required to interpret results. A faulty grid forecast, incorrect maintenance warning and misleading clinical alert create different risks, yet each demands validation, secure system integration and qualified human supervision. AI engineering is therefore best understood as a cyber-physical partnership linking computation, physical processes and accountable professional judgement [38].

Approximately ten years of healthcare experience have taught me that technology succeeds only when it fits the way people actually work. A system may be technically impressive yet fail if it adds unnecessary steps, interrupts patient care or requires staff to repeat information already recorded elsewhere. I have also learned that training cannot be treated as a single event. Users need practical demonstrations, support and opportunities to raise problems after implementation. Incomplete or inconsistent records are a challenge because staff cannot make reliable decisions from information that was never captured correctly. Digital systems should therefore make accurate recording easier, not simply transfer administrative pressure onto clinicians. My experience has also shown that user acceptance improves when healthcare workers are involved early and can see how a system reduces delays, duplication or workload. Evidence on electronic-health-record implementation supports these observations, identifying workflow fit, usability, interoperability, training, leadership and workload as major influences on adoption [39]. Technology should release time for patient care rather than create another burden around it.

Botswana should approach healthcare AI as a staged health-system programme rather than a rapid technology purchase. The first priority is to improve data quality through consistent coding, complete records, reliable identifiers and routine data checks. Existing platforms should then be integrated so that authorised information can move securely between levels of care without repeated manual entry. Staff need continuing training in digital systems, data interpretation, privacy and the limits of AI. Initial applications should be tested through controlled pilot projects with defined objectives, baseline measures and procedures for stopping or correcting unsafe performance. Models must be validated using Botswana data, equipment, languages where relevant and actual clinical workflows before wider deployment. Governance should specify consent, access control, cybersecurity, procurement standards, accountability for decisions and mechanisms for reporting harm. These priorities align with Botswana's AI readiness assessment, which identifies data, skills, infrastructure and inclusive governance as areas requiring continued development [40]. Gradual implementation will produce stronger evidence and reduce the risk of scaling ineffective systems.

10. Conclusion

Artificial intelligence is changing Electrical and Electronic Engineering through forecasting and intelligent control, Mechanical Engineering through predictive maintenance and design optimisation, and Biomedical Engineering through imaging support, monitoring and intelligent devices. In healthcare, it assists professionals to recognise patterns, prioritise attention and manage equipment or services more effectively. Engineering careers increasingly require programming, data analysis, systems integration, cybersecurity, communication and ethical judgement. However, the same technologies introduce risks involving poor data, bias, privacy, cybersecurity, weak validation and unclear responsibility. AI should therefore be treated as an engineering and governance tool rather than an independent decision-maker. Its benefits depend on reliable infrastructure, relevant evidence, competent users and continuing human supervision. Responsible adoption strengthens professional judgement; careless adoption can automate existing weaknesses and create new forms of harm.

For Botswana, the appropriate path is gradual, evidence-based and locally controlled adoption. Healthcare AI should begin with clearly defined problems, dependable infrastructure and small pilot projects whose results can be measured before expansion. Systems must be tested with local data and workflows, protected by strong privacy and cybersecurity controls, and supported by trained staff and reliable maintenance. Imported tools should not be accepted merely because they performed well elsewhere. They must demonstrate safety, fairness and practical value within Botswana's health system. Human-centred design should keep patients, healthcare workers and engineers involved throughout implementation. Sustainable innovation will not come from algorithms alone; it will come from combining useful technology with local evidence, human judgement and clear accountability.

References

1. Huang J. Digital engineering transformation with trustworthy AI towards Industry 4.0: emerging paradigm shifts. Journal of Integrated Design and Process Science. 2023;26(3-4):267-290. https://doi.org/10.3233/JID-229010.
2. Spencer BF Jr, Hoskere V, Narazaki Y. Advances in computer vision-based civil infrastructure inspection and monitoring. Engineering. 2019;5(2):199-222. https://doi.org/10.1016/j.eng.2018.11.030.
3. Peckham O, Raines J, Bulsink E, et al. Artificial intelligence in generative design: a structured review of trends and opportunities in techniques and applications. Designs. 2025;9(4):79. https://doi.org/10.3390/designs9040079.
4. Tanuja GG, Chethana TV. AI in multidisciplinary engineering: a holistic review of technologies and trends. International Research Journal on Advanced Science Hub. 2025. https://doi.org/10.47392/IRJASH.2025.126.
5. Ndlovu K, Stein N, Gaopelo R, Monkge M, Moen L, Molwantwa MC. Experiences, challenges and lessons while implementing a clinical decision support system in Botswana. Oxford Open Digital Health. 2025;3:oqaf014. https://doi.org/10.1093/oodh/oqaf014.
6. Obi CL, et al. Impact of artificial intelligence and digital technology-based diagnostic tools for communicable and non-communicable diseases in Africa. African Journal of Laboratory Medicine. 2024. https://ajlmonline.org/index.php/ajlm/article/view/2516.

7. Segun-Omosehin OA, Omiye JA, Elalfy A, et al. Evaluating the digital health technology landscape in sub-Saharan Africa and its implications for cardiovascular health. npj Cardiovascular Health. 2025;2:20. https://doi.org/10.1038/s44325-025-00055-9.
8. Sukhera J. Narrative reviews: flexible, rigorous, and practical. Journal of Graduate Medical Education. 2022;14(4):414-417. https://doi.org/10.4300/JGME-D-22-00480.1.
9. Green BN, Johnson CD, Adams A. Writing narrative literature reviews for peer-reviewed journals: secrets of the trade. Journal of Chiropractic Medicine. 2006;5(3):101-117. https://doi.org/10.1016/S0899-3467(07)60142-6.
10. Gusenbauer M, Haddaway NR. Which academic search systems are suitable for systematic reviews or meta-analyses? Evaluating retrieval qualities of Google Scholar, PubMed, and 26 other resources. Research Synthesis Methods. 2020;11(2):181-217. https://doi.org/10.1002/jrsm.1378.
11. Snyder H. Literature review as a research methodology: an overview and guidelines. Journal of Business Research. 2019;104:333-339. https://doi.org/10.1016/j.jbusres.2019.07.039.
12. Omitaomu OA, Niu H. Artificial intelligence techniques in smart grid: a survey. Smart Cities. 2021;4(2):548-568. https://doi.org/10.3390/smartcities4020029.
13. Yaraziz MS, Safa NS, Azad MA. Edge computing in IoT for smart healthcare. Applied Intelligence Systems. 2024;16(4). https://doi.org/10.3233/AIS-230009.
14. Zonta T, da Costa CA, da Rosa Righi R, de Lima MJ, da Trindade ES, Li GP. Predictive maintenance in the Industry 4.0: a systematic literature review. Computers & Industrial Engineering. 2020;150:106889. https://doi.org/10.1016/j.cie.2020.106889.
15. Kusiak A. Smart manufacturing. International Journal of Production Research. 2018;56(1-2):508-517. https://doi.org/10.1080/00207543.2017.1351644.
16. Ren R, Hung T, Tan KC. A generic deep-learning-based approach for automated surface inspection. IEEE Transactions on Cybernetics. 2018;48(3):929-940. https://doi.org/10.1109/TCYB.2017.2668395.
17. Kim DW, Jang HY, Kim KW, Shin Y, Park SH. External validation of deep learning algorithms for radiologic diagnosis: a systematic review. Radiology: Artificial Intelligence. 2022;4(2):e210064. https://doi.org/10.1148/ryai.210064.
18. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. Nature Medicine. 2019;25:44-56. https://doi.org/10.1038/s41591-018-0300-7.
19. Yang GZ, et al. The grand challenges of Science Robotics. Science Robotics. 2018;3(14):eaar7650. https://doi.org/10.1126/scirobotics.aar7650.
20. Ribeiro R, et al. A systematic review on wearable-enabled remote health monitoring. DIGITAL HEALTH. 2026;12. https://doi.org/10.1177/20552076261428387.
21. Ministry of Health, Botswana. Health services: clinics and hospitals. https://www.moh.gov.bw/ (accessed 25 August 2026).
22. Botswana Press Agency. Councils offer primary health care from today. DailyNews. 31 March 2025.
23. Kings GY. Analysis of the weaknesses of the decentralised Patient Information Management System and its impact on decision-making by the Ministry of Health and Wellness in Botswana. EBS Journal.
24. Ndlovu K, et al. Acceptance of the District Health Information System Version 2 platform for malaria case-based surveillance by health care workers in Botswana. JMIR Formative Research. 2022;6(3):e32722. https://doi.org/10.2196/32722.

25. Ministry of Health, Botswana. Botswana eHealth Strategy 2020-2024. Gaborone: Ministry of Health; 2020.
26. Ncube B, Mars M, Scott RE. Telemedicine options to address identified health needs in Botswana. DIGITAL HEALTH. 2022;8. https://doi.org/10.1177/20552076221102768.
27. Mabina AT, Malema G, Kombe C. Data warehousing in healthcare: enhancing resource allocation and decision-making in Botswana. Oxford Open Digital Health. 2026;4:oqag006. https://doi.org/10.1093/oodh/oqag006.
28. Bhebe S, de La Harpe R, Kaura D, Kabaso B. Expert perspectives on competencies in health informatics for informatics students. Journal of Health Informatics in Africa. 2024;11(1):22-32. https://doi.org/10.12856/JHIA-2024-v11-i1-365.
29. Alunyu AE, Munene D, Nabukenya J. Towards a digital health curriculum for health workforce for the African region: a scoping review. Journal of Health Informatics in Africa. 2020;7(1):38-54. https://doi.org/10.12856/JHIA-2020-v7-i1-265.
30. UNESCO. AI Competency Framework for Students. Paris: UNESCO; 2024.
31. How AI influences engineering students' competencies development: a literature review. Information and Learning Sciences. 2026;127(3-4):246-267. https://doi.org/10.1108/ILS-12-2025-0231.
32. World Health Organization. Ethics and Governance of Artificial Intelligence for Health: WHO Guidance. Geneva: WHO; 2021.
33. US Food and Drug Administration. Cybersecurity in Medical Devices: Quality System Considerations and Content of Premarket Submissions. Silver Spring, MD: FDA; 2023.
34. Obermeyer Z, Powers B, Vogeli C, Mullainathan S. Dissecting racial bias in an algorithm used to manage the health of populations. Science. 2019;366(6464):447-453. https://doi.org/10.1126/science.aax2342.
35. Asiedu MN, et al. The case for globalizing fairness: a mixed-methods study on colonialism, AI, and health in Africa. Proceedings of the Machine Learning for Healthcare Conference. 2024.
36. World Health Organization. Regulatory Considerations on Artificial Intelligence for Health. Geneva: WHO; 2023.
37. Nasarian E, et al. Designing interpretable machine-learning systems to enhance trust in healthcare: a systematic review and responsible clinician-AI collaboration framework. arXiv. 2023. https://doi.org/10.48550/arXiv.2311.11055.
38. Lee EA. Cyber physical systems: design challenges. Proceedings of the 11th IEEE International Symposium on Object and Component-Oriented Real-Time Distributed Computing. 2008:363-369. https://doi.org/10.1109/ISORC.2008.25.
39. Corbett S, Lehane E, Maruthu R. Nurses' perceptions of facilitators and barriers to their acceptance of electronic health records: a mixed-method systematic review. Journal of Clinical Nursing. 2025;34(8):3085-3100. https://doi.org/10.1111/jocn.17736.
40. UNESCO Office in Harare. Botswana: Artificial Intelligence Readiness Assessment Report. Harare: UNESCO Regional Office for Southern Africa; 2025.