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Medical Artificial Intelligence

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MDD = major depressive disorder. SNRI = serotonin and noradrenaline reuptake inhibitor.

References

1. Kennedy SH, et al. Can J Psychiatry 2016;61:540-560. 2. Boyer P, et al. Int Clin Psychopharmacol 2008;23:243-253. 3. Low Y, et al. Neuropsychiatr Dis Treat 2018;14:567-580. 4. Pristiq® (desvenlafaxine) Prescribing Information. Pfizer Corporation Hong Kong Limited Version **March 2022**

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The Cover Shot

Standing here in tranquil Puerto Madero during PTCOG 63 last June, I watched the sunlit docks of Buenos Aires reflect a truly historic moment. This first global gathering in South America was more than a milestone; it was a catalyst to accelerate access and bridge the vast unmet need for precision radiation oncology. The incredible year of 2025, spanning both Buenos Aires and Hong Kong (the first time hosting PTCOG-Asia Oceania) fostered a seamless bridge of collaboration - from late-breaking data on clinical breakthroughs of proton therapy (PT) versus conventional treatment modalities to the latest learnings from AI-driven treatment planning for PT. Every conversation brought us closer to ensuring the life-changing benefits of PT reach patients across the globe sooner.

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Editorial

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MEDICAL ARTIFICIAL INTELLIGENCE: BALANCING ALGORITHMIC PRECISION WITH CLINICAL EMPATHY

The current issue of *Hong Kong Medical Diary* examines the burgeoning role of Artificial Intelligence (AI) within the clinical landscape, highlighting its transition from theoretical innovation to an indispensable tool for precision medicine. As the healthcare sector increasingly adopts data-driven methodologies, this issue serves to explore the specific applications and ethical considerations of AI across various medical disciplines.

The integration of machine learning and deep learning into clinical workflows represents more than just a technological shift; it necessitates a fundamental re-evaluation of the ethical framework governing the patient-doctor relationship. While the predictive power of AI offers unprecedented opportunities for early intervention and diagnostic accuracy, it also introduces complex challenges regarding transparency, accountability, and the preservation of human empathy in care.

In this issue, our contributors offer a rigorous look at the technological advancements currently redefining patient outcomes:

Liver Diseases & Allergy: We explore AI-driven predictive modelling for Liver Diseases and its capacity to refine diagnostic accuracy in Food Allergy management. These articles highlight the potential for AI to synthesise vast datasets that exceed human cognitive capacity, yet they also prompt us to consider the "black box" problem - where the reasoning behind an algorithm's recommendation remains opaque.

Geriatrics & Neurology: Contributed research details how machine learning is enhancing early biomarker identification and longitudinal monitoring in Dementia. As we deploy these tools, we must remain vigilant about data privacy and the informed consent of vulnerable populations who may not fully grasp how their cognitive data is being utilised.

Integrative Medicine: A critical analysis of the computational frameworks now being applied to standardise and optimise Chinese Medicine. This intersection of ancient wisdom and modern silicon raises unique questions about cultural sensitivity and the risk of over-simplifying holistic practices into binary inputs.

Critical Care: An evaluation of the role of intelligent algorithms in improving safety protocols and perioperative care within Paediatric Anaesthesia. Here, the stakes are at their highest, reminding us that AI must serve as an augmentative tool for the clinician rather than a replacement for professional judgment.

THE ETHICAL IMPERATIVE: BEYOND THE ALGORITHM

As we stand at this technological crossroads, the editorial board believes it is vital to address the ethical pillars that must support the deployment of medical AI in Hong Kong. The primary concern is Algorithmic Bias. AI systems are only as objective as the data upon which they are trained. If training sets lack diversity or reflect historical inequities in healthcare delivery, the resulting algorithms may inadvertently perpetuate disparities in diagnosis and treatment. In a diverse hub like Hong Kong, ensuring that AI tools are validated across local demographic nuances is not merely a technical requirement but a moral one.

Furthermore, the concept of Clinical Accountability undergoes a transformation in the age of AI. When a diagnostic error occurs, where does the liability lie - with the developer of the software, the institution that deployed it, or the physician who followed its guidance? This issue underscores the necessity for "human-in-the-loop" systems, where AI provides the evidence base, but the final clinical decision remains a human responsibility. We must ensure that the convenience of automated suggestions does not lead to "automation bias", where clinicians defer to the machine's output even when their intuition or experience suggests otherwise.

Data Sovereignty and Privacy also remain paramount. The efficacy of AI relies on access to massive quantities of patient data. However, the commodification of health information poses significant risks. As we move toward a more interconnected digital health ecosystem, we must establish robust governance structures that protect patient anonymity while enabling collaborative research necessary to advance the field. Patients must be assured that their data is being used for the advancement of healing, not for the benefit of third-party commercial interests.

Finally, we must consider the impact of AI on the Humanistic Core of Medicine. Medicine is, at its heart, an apprenticeship of empathy. In our Lifestyle Sharing segment, "Healing Notes", we are reminded of this human element through a narrative on the restorative power of music as a balance to the rigours of Emergency Medicine. As AI takes over the more routine, analytical tasks of healthcare - such as image sorting or data entry - it should ideally liberate the clinician to spend more time at the bedside. The "gift of time" provided by AI must be reinvested into the patient-doctor relationship, ensuring that technology serves to enhance, rather than erode, the compassion that defines our profession.

A CALL FOR GOVERNANCE AND REFLECTION

The articles contained in this issue demonstrate that Hong Kong is at the forefront of this digital revolution. However, the rapid pace of innovation often outstrips the development of regulatory and ethical guidelines. It is our hope that *Hong Kong Medical Diary* serves as a forum not only for celebrating technical success but also for rigorous debate on how these tools should be governed.

We trust this issue provides a valuable academic resource for clinicians seeking to navigate the integration of digital health into the Hong Kong medical ecosystem. The transition to AI-augmented medicine is inevitable; our task is to ensure it is also equitable, transparent, and profoundly human.

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Atopic Dermatitis (AD)
- Moderate-to-severe AD in adults and adolescents ≥12 years old†
- Severe AD in children 6 months to 11 years old†

6+ months

Asthma
- In adults and adolescents ≥12 years old as add-on maintenance treatment for severe asthma with Type 2 inflammation*
- In children 6 to 11 years old as add-on maintenance treatment for severe asthma with Type 2 inflammation^

6+ years

Chronic rhinosinusitis with nasal polyposis (CRSwNP)
- As an add-on therapy with intranasal corticosteroids for the treatment of adults with severe CRSwNP#

18+ years

Prurigo Nodularis (PN)
- Moderate-to-severe PN in adults who are candidates for systemic therapy

18+ years

Eosinophilic Esophagitis (EoE)
- In adults and adolescents ≥12 years old weighing ≥40 kg‡

12+ years

Newly approved

Chronic Obstructive Pulmonary Disease (COPD)
- As add-on maintenance treatment with other medicines for adults with uncontrolled COPD§

18+ years

† Candidates for systemic therapy
* Characterised by raised blood eosinophils and/or raised FeNO, who are inadequately controlled with high dose ICS plus another medicinal product for maintenance treatment.
^ Characterised by raised blood eosinophils and/or raised FeNO, who are inadequately controlled with medium to high dose ICS plus another medicinal product for maintenance treatment.
# For whom therapy with systemic corticosteroids and/or surgery do not provide adequate disease control.
‡ Those who are inadequately controlled by, are intolerant to, or who are not candidates for conventional medicinal therapy.
§ Characterised by raised blood eosinophils, on a combination of an inhaled corticosteroid (ICS), a long acting beta2-agonist (LABA), and a long-acting muscarinic antagonist (LAMA), or on a combination of a LABA and a LAMA if ICS is not appropriate.

Abbreviations: AD=atopic dermatitis; COPD = chronic obstructive pulmonary disease; CRSwNP= chronic rhinosinusitis with nasal polyps; EoE= eosinophilic esophagitis; FeNO=fractional exhaled nitric oxide; ICS=inhaled corticosteroids; LABA = long acting beta2-agonist; LAMA = long acting muscarinic antagonist; PN=prurigo nodularis.

References:
1. Guttman-Yassky E, et al. J Allergy Clin Immunol. 2019;143(1):155-172. 2. Gandhi NA, et al. Nat Rev Drug Discov. 2016;15(1):35-50 3.DUPIXENT® Hong Kong Prescribing Information

Presentation: Dupilumab solution for injection in a pre-filled syringe with needle shield. **Indications:** Atopic Dermatitis (AD): Moderate-to-severe AD in adults and adolescents ≥12 years who are candidates for systemic therapy; severe atopic dermatitis in children 6 months to 11 years old who are candidates for systemic therapy. Asthma: In adults and adolescents ≥12 years as add-on maintenance treatment for severe asthma with type 2 inflammation characterised by raised blood eosinophils and/or raised FeNO, who are inadequately controlled with high dose ICS plus another medicinal product for maintenance treatment. In children 6 to 11 years old as add-on maintenance treatment for severe asthma with type 2 inflammation characterised by raised blood eosinophils and/or raised FeNO, who are inadequately controlled with medium to high dose ICS plus another medicinal product for maintenance treatment. For 300 mg only – Chronic rhinosinusitis with nasal polyposis (CRSwNP): As an add-on therapy with intranasal corticosteroids for the treatment of adults with severe CRSwNP for whom therapy with systemic corticosteroids and/or surgery do not provide adequate disease control. Prurigo Nodularis (PN): Moderate-to-severe PN in adults who are candidates for systemic therapy. Eosinophilic esophagitis (EoE): In adults and adolescents ≥12 years, weighing ≥40 kg, who are inadequately controlled by, are intolerant to, or who are not candidates for conventional medicinal therapy. Chronic obstructive pulmonary disease (COPD): In adults as add-on maintenance treatment for uncontrolled COPD characterised by raised blood eosinophils on a combination of ICS, LABA, and LAMA, or on a combination of LABA and LAMA if ICS is not appropriate. **Dosage & Administration:** Subcutaneous injection. AD adults: Initial dose of 600 mg (two 300 mg injections), followed by 300 mg Q2W. AD adolescents (12-17y/o): Body weight <60 kg- initial dose of 400 mg (two 200 mg injections), followed by 200 mg Q2W. Body weight ≥60 kg- same dosage as adults. AD children (6-11y/o): Body weight 15kg–<60 kg- initial dose of 300 mg on Day 1 follow by 300 mg on Day 15, then 300mg Q4W. Body weight ≥60 kg- same dosage as adults. ^The dose may be increased to 200 mg Q2W in patients with body weight of 15 kg–< 60 kg based on physician's assessment. AD children (6 months-5y/o): Body weight 5kg–<15 kg- initial dose of 200 mg, then 200 mg Q4W. Body weight 15kg–<30 kg- initial dose of 300 mg, then 300 mg Q4W. Dupilumab can be used with or without topical corticosteroids. Topical calcineurin inhibitors may be used, but should be reserved for problem areas only, e.g. face, neck, intertriginous and genital areas. Consider discontinuing treatment in patients who have shown no response after 16 weeks. Asthma adults and adolescents: Initial dose of 400 mg, followed by 200 mg Q2W. For patients with severe asthma and on oral corticosteroids or with severe asthma and co-morbid moderate-to-severe AD or adults with co-morbid severe CRSwNP- initial dose of 600 mg, followed by 300 mg Q2W. Asthma children (6-11y/o): Body weight 15kg–<30 kg- 300 mg Q4W. Body weight 30kg–<60 kg- 200 mg Q2W; or 300 mg Q4W. Body weight ≥60 kg- 200 mg Q2W. For paediatric patients (6-11y/o) with asthma and co-morbid severe atopic dermatitis, as per approved indication, the recommended dose should follow AD children (6-11y/o). Patients receiving concomitant oral corticosteroids may reduce steroid dose gradually once clinical improvement with dupilumab has occurred. The need for continued dupilumab therapy should be considered at least annually as determined by a physician. CRSwNP: Initial dose of 300 mg, followed by 300 mg Q2W. Consider discontinuing treatment in patients who have shown no response after 24 weeks. PN: Initial dose of 600 mg (two 300 mg injections), followed by 300 mg Q2W. Dupilumab can be used with or without topical corticosteroids. Consider discontinuing treatment in patients who have shown no response after 24 weeks. EoE: 300 mg QW. Dupilumab 300 mg QW has not been studied in patients with EoE weighing <40 kg. Dosing beyond 52 weeks has not been studied. COPD: 300 mg Q2W. Consider discontinuing treatment in patients who have shown no response after 52 weeks. For Missed dose instructions, please refer to the full prescribing information. **Contraindications:** Hypersensitivity to dupilumab or any of the excipients. **Precautions:** Not be used to treat acute symptoms, acute exacerbations of asthma or COPD, acute bronchospasm or status asthmaticus. Do not discontinue corticosteroids abruptly upon start of dupilumab. Reduction should be gradual and performed under supervision of a physician; it may be associated with systemic withdrawal symptoms and/or unmask conditions previously suppressed by systemic corticosteroid therapy. Biomarkers of type 2 inflammation may be suppressed by systemic corticosteroid use. If systemic hypersensitivity reaction occurs, discontinue dupilumab and initiate appropriate therapy. Be alert to vasculitic rash, worsening pulmonary symptoms, cardiac complications, and/or neuropathy presenting in patients with eosinophilia. Treat pre-existing helminth infections before initiating dupilumab. If patients become infected while receiving dupilumab and do not respond to anti-helminth treatment, discontinue dupilumab until infection resolves. Cases of enterobiasis were reported in children 6 to 11 years old in the paediatric asthma development program. Advise patients to promptly report new onset or worsening eye symptoms. Patients who develop conjunctivitis, dry eye and keratitis that does not resolve following standard treatment should undergo ophthalmological examination. Sudden changes in vision or significant eye pain that does not settle warrant urgent review. Patients with comorbid asthma should not adjust or stop asthma treatments without consultation with physicians. Carefully monitor patients after discontinuation of dupilumab. Avoid using live and live attenuated vaccines concurrently with dupilumab. Patients should be brought up to date with immunisations before starting dupilumab. **Drug Interactions:** Immune responses to TdaP vaccine and meningococcal polysaccharide vaccine were assessed. Patients receiving dupilumab may receive concurrent inactivated or non-live vaccinations. **Pregnancy and lactation:** Should be used during pregnancy only if potential benefit justifies potential risk to foetus. Unknown whether dupilumab is excreted in human milk or absorbed systemically after ingestion. Decision must be made whether to discontinue breast-feeding or dupilumab taking into account benefit of breast feeding for the child and benefit of therapy for the woman. **Undesirable effects:** Most common adverse reactions reported- injection site reactions, conjunctivitis, conjunctivitis allergic, arthralgia, oral herpes, eosinophilia and injection site bruising. Safety profile observed in adolescents and children 6 months to 11 years old consistent with that seen in adults. For other undesirable effects, please refer to the full prescribing information. **Preparation:** 2 x 300mg/2ml in pre-filled syringe with needle shield, 2 x 200mg/1.14ml in pre-filled syringe with needle shield. **Legal Classification:** Part 1, First & Third Schedules Poison **Full prescribing information is available upon request.**

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Artificial Intelligence in Liver Diseases

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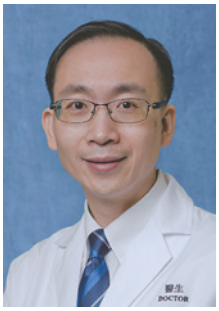

Dr Soe Thiha MAUNG Dr Vincent Wai-sun WONG

This article has been selected by the Editorial Board of the Hong Kong Medical Diary for participants in the CME programme of the Medical Council of Hong Kong (MCHK) to complete the following self-assessment questions in order to be awarded 1 CME credit under the programme upon returning the completed answer sheet to the Federation Secretariat on or before 30 June 2026.

INTRODUCTION

Artificial intelligence (AI), encompassing machine learning and deep learning approaches applied to large-scale datasets, has already transformed medicine, with marked effects in hepatology[1]. The convergence of powerful algorithms and ever-growing "big data" repositories (including electronic health records, multimodal imaging, histopathology slides, laboratory time series and genomic data) has created unprecedented opportunities to enhance diagnostic precision, risk stratification and prognostication for patients with liver disease. In hepatology, AI tools have been developed to assist in interpreting liver pathology and imaging, where they are already playing a pivotal role in detecting cirrhotic complications and identifying hepatocellular carcinoma (HCC). Such applications can reduce interobserver variability, increase sensitivity for early disease, and accelerate reporting workflows in clinical practice.

Beyond diagnosis, AI-driven predictive models are being created to support personalised treatment recommendations and individualised risk assessments, thereby aiding informed clinical decision-making. The ability of AI to ingest and analyse time-series data (for example, longitudinal laboratory measurements, serial imaging metrics and evolving comorbidities) strengthens its utility for monitoring disease progression and assessing response to therapy. This temporal capability is especially pertinent to chronic liver diseases, where early recognition of trajectory changes may permit interventions that materially alter outcomes.

The role of AI in hepatology continues to broaden into emerging domains, such as the analysis of patient-reported outcomes, integration of genomic and multi-omics data, and real-time monitoring of liver function using wearable and bedside devices. As methodological rigour and data governance mature, it is becoming increasingly apparent that AI has the potential not only to refine how we diagnose and manage liver disease but also to deepen our understanding of disease mechanisms. This review surveys current clinical and research applications, and considers potential benefits, limitations and future directions in this rapidly evolving field (Fig. 1).

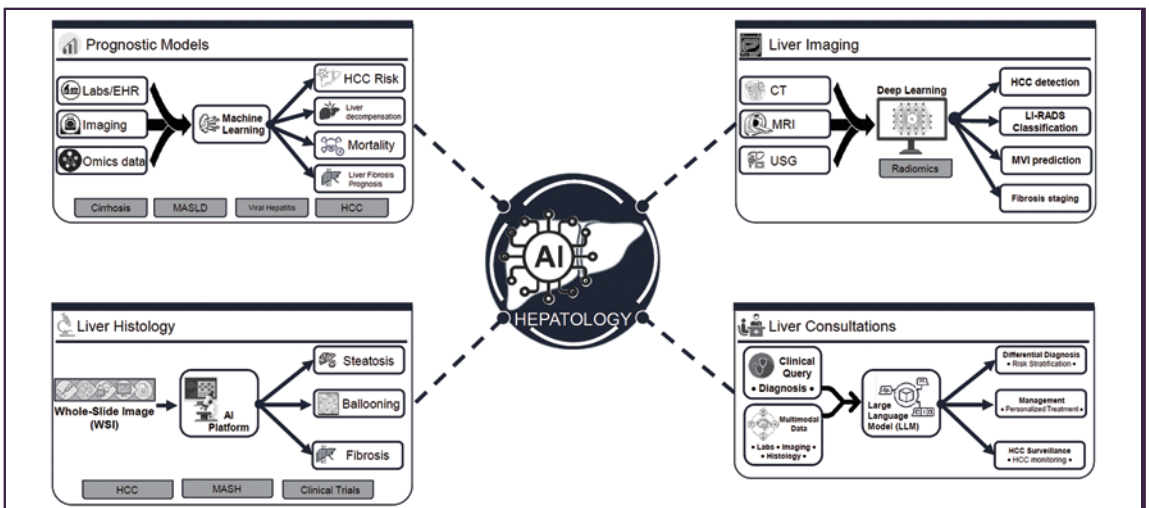

Fig. 1: Applications of artificial intelligence (AI) across key domains of hepatology.
Footnotes: CT, computed tomography; EHR, electronic health record; HCC, hepatocellular carcinoma; MASH, metabolic dysfunction-associated steatohepatitis; MASLD, metabolic dysfunction-associated steatotic liver disease; MRI, magnetic resonance imaging; MVI, microvascular invasion; LI-RADS, Liver Imaging Reporting and Data System; USG, ultrasonography (Developed by the authors)

AI IN PROGNOSTIC MODELS

Standard prognostic scoring systems for liver disease remain central to clinical decision-making. However, their reliance on a limited set of predefined variables and predominantly linear statistical formulas restricts their ability to fully capture the complexities of liver disease. Specifically, they may not adequately reflect temporal changes or the intricate interactions among clinical, biochemical, and imaging parameters, which may lead to ultimately compromising the accuracy of personalised risk assessments[2].

Types of AI Approaches in Prognostic Modelling

In this context, AI-based prognostic modelling offers a more flexible and data-driven alternative. Researchers have successfully implemented numerous machine learning algorithms in liver disease, ranging from random forests and support vector machines to gradient boosting and deep learning networks. Unlike traditional scores, these computational models excel at mapping non-linear correlations and multidimensional interactions across expansive datasets, encompassing clinical, biochemical, and omics profiles[3]. Furthermore, many AI models also incorporate variable importance ranking, which helps identify the most influential predictors while maintaining model efficiency. By integrating heterogeneous and longitudinal data, AI-based models provide a more dynamic and individualised framework for prognostic assessment, with the potential to improve risk stratification and support more tailored clinical decision-making in hepatology[4].

Key Clinical Applications of AI-based Models in Hepatology

AI-based prognostic models are increasingly shaping risk assessments across major liver diseases, including cirrhosis, metabolic dysfunction-associated steatotic liver disease (MASLD), and viral hepatitis. For cirrhosis, these models integrate clinical and biological data to improve the prediction of mortality, decompensation, and survival, while also enabling non-invasive evaluation of portal hypertension and automated body composition analysis[5]. Regarding MASLD, AI facilitates the earlier identification of patients at risk of fibrosis progression, hepatic decompensation, HCC, and extrahepatic outcomes, such as cardiovascular and renal events, by leveraging longitudinal clinical, laboratory, histological, and molecular data[4]. Similarly, in viral hepatitis, machine learning directly sharpens clinical predictions regarding cirrhosis, HCC development, and disease-specific mortality by strategically merging distinct virologic markers with standard routine diagnostic findings[6]. Across these conditions, AI-based models offer more flexible and dynamic risk stratification than conventional scores, allowing for updated prognoses over time. This supports more individualised surveillance strategies, informs treatment prioritisation, and enables closer monitoring of high-risk patients for HCC. Collectively, these advances highlight the growing role of AI in delivering more precise and patient-centred prognostic assessments in hepatology.

Strengths, Limitations and Clinical Impact

While these advances highlight the clinical potential of AI, the clinical translation of these tools remains contingent upon rigorous methodological scrutiny and ethical implementation. Robust model development requires attention to methodological quality, including deliberate prevention of data leakage, and transparent methodologies for managing missing data. Furthermore, the establishment of clinical reliability requires robust validation protocols, specifically emphasising external validation across diverse, multicentre cohorts to ensure broad generalisability and longitudinal stability. Addressing inherent algorithmic bias and prioritising model interpretability are equally paramount to maintaining equitable patient care and securing essential clinician confidence. In practice, AI should function most effectively as adjunctive decision-support tool that complements, rather than replaces, expert clinical judgment. When integrated thoughtfully into clinical workflows, clinicians can substantially enhance diagnostic and prognostic efficiency while simultaneously preserving patient safety and ensuring the clinical relevance of routine care[1].

Future Directions

Building on these considerations, future studies should focus on embedding AI models more closely within electronic health records and leveraging richer longitudinal and multimodal data, including genomics and patient-reported outcomes. Improving model transparency through explainable AI will be key to strengthening clinical confidence. In parallel, approaches such as decentralised federated learning, rigorous external validation, and prospective multicentre studies are needed to enhance generalisability, safety, and equity while ensuring smooth integration into real-world clinical care delivery workflows.

AI IN RADIOLOGICAL IMAGING

Radiological imaging plays a pivotal function within hepatology, supporting the non-invasive diagnosis of HCC, surveillance of high-risk populations, disease staging, and assessment of treatment response. Despite its utility, several challenges remain to be addressed. Interpretation can vary between radiologists, even with standardised systems such as the Liver Imaging Reporting & Data System (LI-RADS). In addition, small or obscure lesions frequently go undetected, and image review can be time-consuming, potentially affecting diagnostic consistency and operational efficiency in routine clinical practice[7].

Core AI Techniques in Liver Imaging

To address these limitations, AI has been increasingly applied in liver imaging, particularly through computer vision and deep learning techniques for automated lesion detection, segmentation, and characterisation[1]. Concurrently, radiomics allows conventional images to be converted into high-dimensional quantitative data by capturing features related to texture, shape,

and signal intensity. Recently, synergistic models that combine radiomics with deep learning have emerged, offering more consistent and biologically relevant image interpretation[8]. Together, these methods can detect subtle patterns that may not be apparent on visual review, supporting more accurate diagnosis and enhancing the robustness of clinical decisions.

Clinical Applications of AI-assisted Liver Imaging

Expanding upon these innovations, AI-based imaging tools are increasingly used to detect and monitor liver lesions, particularly early-stage HCC, using ultrasound, CT, and MRI. They can improve lesion visibility, assist with automated localisation and classification, and minimise occurrences of overlooked HCCs[9]. In practice, this supports earlier diagnosis, more consistent surveillance, and better selection of patients for further evaluation and timely therapeutic interventions. Beyond detection, AI-based radiomics offers incremental utility by correlating radiographic features with underlying biology. It can non-invasively predict microvascular invasion, tumour aggressiveness, and recurrence risk, thereby helping to refine individualised prognostic assessment. Within clinical workflows, these tools also support tumour segmentation, guide treatment strategies, and improve treatment response evaluation beyond conventional criteria. Notably, MRI-based radiomics has shown promising performance in predicting recurrence and microvascular invasion, supporting precision management of HCC[8]. Beyond the evaluation of focal hepatic lesions, AI plays an important role in liver fibrosis assessment and quantification. By synthesising cross-sectional modalities with elastography, pathology, and clinical data, non-invasive detection and staging of fibrosis are reinforced. This may reduce reliance on biopsy, improve diagnostic reproducibility, and enable earlier identification of clinically significant fibrosis or cirrhosis, thereby strengthening risk stratification in chronic liver disease[10].

Limitations and Challenges of AI in Liver Imaging

Despite these promising developments, several challenges limit the routine implementation of AI into liver imaging workflows. Many models rely on large, well-annotated datasets, which are often unattainable, and their performance can be affected by statistical bias, overfitting, or heterogeneity between centres, scanners, and demographics. The accuracy may also decline in more complex real-world settings. Furthermore, the limited interpretability of many AI models can reduce the confidence of clinicians. Practical issues, including the risk of data leakage, difficulties in integrating AI into existing workflows, and ongoing regulatory requirements, remain important barriers to more extensive clinical adoption[1].

Future Directions

Moving forward, progress in AI-assisted liver imaging will depend on stringent validation and seamless assimilation within clinical practice environments. Prospective multicentre studies and robust external validation are needed to confirm performance across diverse settings[9]. Deep integration with radiology and hepatology workflows, including electronic health records and picture archiving and communication systems, remains highly indispensable. Standardised imaging protocols, interoperable data, and privacy-preserving approaches, such as federated learning, will strengthen both reliability and scalability. Advances in radiomics and AI-assisted imaging modalities with enhanced diagnostic precision, such as abbreviated MRI may further enhance the surveillance and therapeutic decision-making for HCC. Equally important, future work should address interpretability, regulatory considerations, cost-effectiveness, and infrastructure sustainability to ensure that AI tools are not only accurate but also secure, practical, and credible throughout routine management paradigms.

AI IN LIVER HISTOLOGY

The digitisation of histopathology and advances in computational image analysis have enabled quantitative, reproducible measures of tissue features that were previously assessed subjectively, opening new avenues for clinical care, trial enrollment and translational research[11].

Evolution of Digital Pathology in Liver Disease

Digitally scanned whole-slide images and label-free imaging modalities (for example, second harmonic generation/two-photon excitation) now permit high-resolution, computer-aided interrogation of hepatobiliary tissue[12]. These technologies underpin a move from semiquantitative ordinal scoring towards continuous, quantitative metrics that capture subtle histological changes. The shift is particularly salient in metabolic dysfunction-associated steatohepatitis (MASH), where regulatory agencies accept histological endpoints of resolution of MASH and fibrosis improvement for accelerated approval pathways. Such endpoints demand accurate, reproducible assessment, yet traditional pathology faces well-documented challenges: inter- and intrarater variability is often poor, especially for ballooning, a defining but subjective feature of MASH. In practice, disagreement among pathologists can materially affect trial eligibility and histological response classification, thereby increasing trial complexity and cost.

AI-assisted Scoring of Liver Histology

Several AI platforms (for example, PathAI/AIM-MASH, Histoindex, FibroNest, MorphoQuant) have demonstrated improved reproducibility and, in many cases, superior accuracy compared with individual human readers. AIM-MASH notably became the first AI tool to receive regulatory qualification from both the Food and Drug Administration and the European Medicines Agency for assessing MASH histology in clinical trials. Unlike ordinal scoring systems,

AIM-MASH yields continuous measures for each histological feature, enhancing sensitivity to incremental change that may be missed by crude categorical scales[13]. This granularity could reduce sample sizes and shorten trial timelines by detecting treatment effects earlier or more reliably.

Nonetheless, important questions remain. Current AI models are typically trained against human-scored biopsies, and therefore inherit limitations of the reference standard. There is a compelling rationale to pursue models trained on hard clinical outcomes to provide unbiased, prognostically relevant measures. The regulatory landscape also poses challenges: while iterative model refinement is integral to AI development, regulators expect a "finalised" model for qualification and have signalled that major changes may require requalification - yet criteria for what constitutes a major change are not fully defined. Furthermore, reliance on a single platform is undesirable; cross-platform comparisons and independent validation will be essential to ensure generalisability across institutions and staining protocols.

Applications in Hepatocellular Carcinoma

Digital pathology and pathomics have likewise advanced research in HCC[14]. Deep-learning approaches on whole-slide images can distinguish HCC from dysplastic nodules or cholangiocarcinoma and predict key histological features such as tumour differentiation and microvascular invasion with area under the receiver-operating characteristic curve (AUROC) often exceeding 0.8. Pathomics has also been used to predict molecular alterations and to build prognostic models for recurrence and response to therapies including immunotherapy, although reported performance varies (AUROC ~0.6-0.9) and requires further external validation.

Emerging Directions

Generative and multimodal models, including visual-language models, are being explored to integrate imaging with clinical and molecular data. Examples such as HepaPathGPT, which combines radiological segmentation and non-invasive pathological prediction to generate structured reports, point towards a future where multimodal AI provides rapid, clinically actionable insights[15]. As the field matures, rigorous prospective validation, transparent reporting, and thoughtful regulatory engagement will be critical to translate digital imaging AI from promising research tools into trustworthy components of hepatology practice.

AI IN LIVER CONSULTATIONS

AI in clinical consultations for liver disease holds considerable promise for enhancing diagnostic accuracy, streamlining risk assessment and supporting shared decision-making[16]. In routine practice, clinicians face increasingly large volumes of longitudinal data such as laboratory trends, imaging reports, medication changes and comorbidity trajectories that can be challenging to integrate rapidly at the bedside. Properly designed AI systems can synthesise these multimodal data to provide timely risk stratification, flag patients at high risk of decompensation, suggest differential diagnoses and generate personalised management options. When embedded within electronic health records (EHRs), such tools have the potential to reduce cognitive load, prompt appropriate investigations and standardise care pathways across institutions.

However, translating these capabilities into safe, equitable clinical consultations requires careful attention to limitations that have emerged from early experience. A central challenge is the dependence of AI models on the quality and representativeness of the training data. Models trained on skewed datasets may underperform in under-represented subgroups, perpetuating or exacerbating existing health inequalities. For example, reproduction of several serum-parameter models in a widely used liver disease dataset revealed sex disparities in diagnostic performance driven by imbalanced biochemical marker representation[17]. Such bias risks misclassification of disease in women or minority populations and undermines clinician confidence in the tool.

Closely related is the risk of overfitting and data leakage. Overfitted models appear highly accurate on internal testing but generalise poorly to new populations; inadvertent leakage of outcome information into training can inflate performance estimates and mislead deployment decisions. Rigorous study design, external validation across diverse cohorts and transparent reporting of dataset composition are therefore essential before clinical use.

Another practical consideration is the complementary role of clinicians. Some AI models, particularly those based on a single data modality, may achieve good specificity yet lack sensitivity compared with experienced physicians who integrate clinical context. For instance, a contrast-enhanced ultrasound AI algorithm demonstrated excellent specificity for benign versus malignant lesion classification but had lower sensitivity than seasoned clinicians when diagnosing complex entities such as hepatocellular carcinoma or metastases. This finding emphasises that, at present, AI is most valuable as an adjunct - providing second opinions, triaging cases and highlighting discordant findings - rather than replacing expert judgement.

Finally, the phenomena of hallucination (generation of factually incorrect outputs) and privacy-sensitive errors are particularly concerning in clinical consultations. Misleading recommendations or inappropriate explanations can erode trust and result in harmful management decisions. Robust safeguards, including human-in-the-loop review, explainability tools, audit trails and conservative deployment in high-stakes scenarios, are therefore mandatory.

CONCLUSIONS AND FUTURE DIRECTIONS

In conclusion, the integration of AI into hepatology offers substantial promise for both research and clinical care. Considerable progress has been made,

particularly in digital imaging, where AI-driven analysis of histological slides and radiological scans is most mature. Models capable of predicting disease status, stratifying risk and prognosticating clinical outcomes are increasingly available, and regulatory milestones such as qualified tools for MASH histology attest to the field's momentum. Yet translating these advances into routine practice requires careful resolution of multiple technical, organisational and ethical challenges.

A primary hurdle is practical integration with existing clinical workflows and EHR systems[18]. Interoperability across heterogeneous EHR platforms, the costs of implementation and ongoing maintenance, and alignment with diverse regulatory regimes must be addressed to allow widespread adoption. Clear frameworks for clinical liability and responsibility are also required so that clinicians and institutions can deploy AI with confidence.

Patient privacy and data governance are central concerns. Privacy-preserving techniques such as federated learning, differential privacy and homomorphic encryption offer viable strategies to train and deploy models while minimising the movement or exposure of identifiable data[19]. These approaches can help reconcile the twin imperatives of robust model performance and legal-ethical compliance.

Equally important are methodological issues. AI models must be trained and validated on representative, high-quality datasets to avoid bias and overfitting; external, prospective validation and head-to-head comparisons between platforms are essential; and where possible, models should be anchored to hard clinical outcomes rather than imperfect human reference standards. Transparency in model development, explainability tools to aid clinician interpretation, and human-in-the-loop workflows will foster trust and safer deployment.

Looking ahead, the hepatology community should prioritise collaborative governance, standardised reporting, and multicentre studies that test AI across diverse populations and care settings. If these steps are taken, AI has the potential to refine diagnostics, personalise therapy, optimise trial design and deepen mechanistic understanding of liver disease. The path forward is promising but demands coordinated effort across clinicians, data scientists, regulators and patients to realise AI's benefits equitably and safely.

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MCHK CME Programme Self-assessment Questions

Please read the article entitled "Artificial Intelligence in Liver Diseases" by Dr Soe Thiha MAUNG and Dr Vincent Wai-sun WONG and complete the following self-assessment questions. Participants in the MCHK CME Programme will be awarded CME credit under the Programme for returning completed answer sheets via fax (2865 0345) or answer link: https://forms.gle/duwDQpheZZ64S5oe8 or by mail to the Federation Secretariat on or before 30 June 2026. Answers to questions will be provided in the next issue of The Hong Kong Medical Diary. (Address: Duke of Windsor Social Service Bldg., 4/Fl., 15 Hennessy Rd., Wan Chai. Enquiry: 2527 8898)

Questions 1 - 10: Please answer T (true) or F (false)

1. **Compared with traditional statistical methods, one major limitation of artificial intelligence (AI) is its inability to handle longitudinal and time-series data.**
2. **AI has been applied to predict the development of metabolic dysfunction-associated steatotic liver disease, cirrhosis, cirrhotic complications, and hepatocellular carcinoma.**
3. **The Liver Imaging Reporting & Data System (LI-RADS) should be used to evaluate liver lesions on imaging and determine the likelihood of malignancy.**
4. **AI can detect and characterise liver lesions on computed tomography but not ultrasonography or magnetic resonance imaging.**
5. **Radiomic features at the time of hepatocellular carcinoma diagnosis can predict the risk of tumour recurrence after liver resection.**
6. **Macrovascular but not microvascular invasion predicts hepatocellular carcinoma recurrence.**
7. **AI-assisted assessment of liver histology requires standard staining with high quality.**
8. **A drug for metabolic dysfunction-associated steatohepatitis (MASH) may receive accelerated approval for clinical use if it demonstrates MASH resolution and liver fibrosis improvement on serial liver biopsies.**
9. **AI hallucination refers to the detection of psychotic symptoms in patients with suspected psychiatric illness.**
10. **Patient privacy and data governance are key issues to consider when applying AI in clinical practice.**

ANSWER SHEET FOR JUNE 2026

Please return the completed answer sheet to the Federation Secretariat on or before 30 June 2026 for documentation. 1 CME point will be awarded for answering the MCHK CME programme (for non-specialists) self-assessment questions.

Artificial Intelligence in Liver Diseases

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Answer Link

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7 ☐ 8 ☐ 9 ☐ 10 ☐

Name (block letters):_____ HKMA No.: _____ CDSHK No.: _____

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Answers to May 2026 Issue

Vascular Access for Endovascular Intervention and Its Complications

1. T 2. F 3. F 4. F 5. T 6. T 7. F 8. F 9. F 10. T

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A ONCE-DAILY oral atypical antipsychotic[1]

Proven Efficacy in Bipolar I Depression[2,3]

Reduction in Depressive Symptoms[2-3]

44%↓ greater reduction in MADRS score in monotherapy*

27%↓ greater reduction in MADRS score in adjunctive therapy*^

Improvement in Functional Impairment[2-3]

50%↓ in SDS in monotherapy*

35%↓ in SDS in adjunctive therapy*^

Alleviation of Anxiety Symptoms[2-3]

48%↓ in HAM-A in monotherapy with 20 - 60 mg/day*

33%↓ in HAM-A in adjunctive therapy*^

Better Quality of Life (QoL)[2-3]

50%↑ QoL enjoyment and satisfaction in monotherapy*

39%↑ QoL enjoyment and satisfaction in adjunctive therapy*^

*compared to placebo at week 6 ^with lithium/valproate

Well-established Safety Profile[2-4]

No or Minimal Noticeable Effect on Weight and Metabolic Parameters - BMI, Prolactin, ECG parameters[2,4]

Low Occurrence of Serious AEs[2,3]

Indications[1]

No initial dose titration is required[1]

SCHIZOPHRENIA

- Adults 40-160 mg/day
- Adolescents (15-17 years) 40-80 mg/day

BIPOLAR I DEPRESSION

- Adults 20-120 mg/day
- Adolescents (13-17 years) 20-80 mg/day

Abbreviations: BMI= Body Mass Index, ECG= Electrocardiography, HAM-A= Hamilton Anxiety Rating Scale, MADRS= Montagometry-Asberg Depression Rating Scale, QoL= Quality of Life, SDS= Sheehan Disability Scale

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Artificial Intelligence in Food Allergy

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Artificial intelligence (AI) - encompassing specialised methods such as machine learning and deep learning - has emerged as one of the most transformative innovations in modern medicine, leveraging its capacity to uncover complex, non-linear patterns in data to drive meaningful advances across diagnosis, prognostication, treatment selection, drug development, and healthcare delivery[1]. Among the most notable advances are deep learning–based medical image interpretation, AI-assisted pathology and dermatology classification, clinical prediction models, wearable and remote monitoring systems, and AI-enabled drug discovery. By combining multimodal clinical, imaging, genomic, and behavioural data, AI is increasingly enabling earlier detection of disease, more individualised care, and improved operational efficiency across healthcare systems.

The implementation of AI in allergy has been more limited compared to established domains such as medical imaging and clinical oncology in Hong Kong[2,3]. Emerging applications in the field of food allergy (FA) are nonetheless promising - spanning allergy risk prediction, diagnostic decision support, and the identification of novel biomarkers (Table 1) - and highlight a unique opportunity to improve how clinicians predict, diagnose, and manage FA (Fig. 1). Successful integration of these AI systems could meaningfully improve patient outcomes while alleviating pressure on an already stretched healthcare system.

COMPUTATIONAL ALLERGEN IDENTIFICATION

The computational identification of allergenic proteins represents a pivotal upstream application of AI, providing the molecular groundwork upon which clinical prediction and diagnostic tools are built. AI models can analyse protein sequences and classify whether a given protein is likely to be allergenic - enabling earlier risk identification than conventional laboratory-based testing and offering a scalable tool for screening novel foods, engineered proteins, and potential cross-reactive allergens. In a notable recent advance, investigators at The Chinese University of Hong Kong (CUHK) developed the Allergen Prediction with Protein Language Model (APPLM), which leverages the xTrimoPGLM protein language model - a large-scale AI architecture trained on vast protein sequence databases to capture deep structural and functional relationships - and

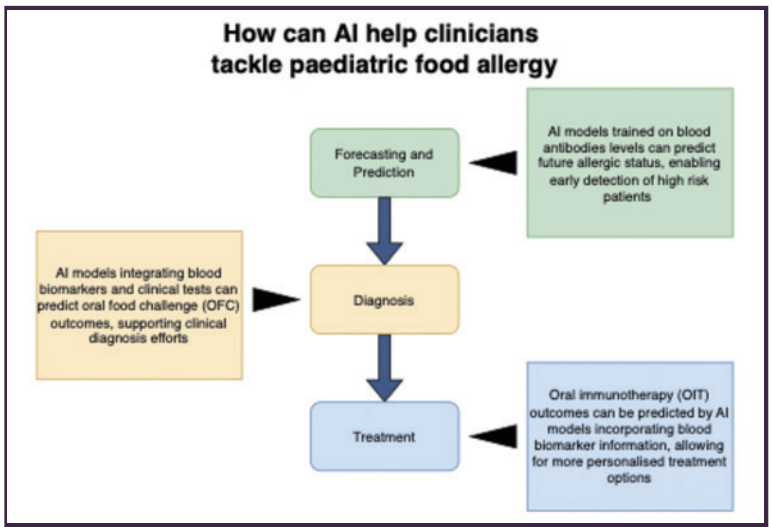

Fig. 1: Schematic overview of how AI can help clinicians tackle paediatric food allergy. Artificial intelligence, AI (Developed by the authors)

Table 1: Summary of AI-based food allergy prediction studies on clinical cohorts (Developed by the authors)

Author and year	Allergen	Model architecture	Prediction target	Training feature	Internal validation	External validation
Suárez-Fariñas et al., 2018[17]	Milk	Elastic net	SU after OIT cessation	6 milk epitope-sIgE	AUROC: 0.95	not available
Suprun et al., 2020[23]	Peanut	Random forest	Allergic status at 4+ years (Positive OFC and PN-sIgE ≥ 0.35 kUA/L or SPT wheal size ≥ 3mm, or PN-sIgE ≥ 15 kUA/L standalone)	Ara h 1, 2, and 3 epitope-sIgE and peanut-sIgE at year 2	AUROC: 0.87	not available
Kuniyoshi et al., 2020[14]	Egg	Logistic regression and SVM	OFC challenge outcome (pass versus fail)	Demographic, Egg-sIgE	Accuracy: 72 %, Sensitivity: 0.68 – 0.7, Specificity: 0.73 – 0.74, AUROC: 0.82 – 0.83	not available
Machnes-Maayan et al., 2022[13]	Sesame	Decision Tree	OFC challenge outcome (pass versus fail)	Demographic, SPT wheal and flare size	PPV: 0.9585, NPV: 0.9585	not available
Zhang et al., 2022[24]	Peanut, Egg, and Milk	Random forest and LUCCK	OFC challenge outcome (pass versus fail)	Demographic, comorbidities, OFC reason, SPT wheal and flare size, total and allergen-sIgE	Accuracy: 93 % – 98 %, Sensitivity: 0.95 – 0.98, Specificity: 0.72 – 0.95, AUROC: 0.91 – 0.94	not available
Grinek et al., 2024[10]	Peanut	Elastic net	OFC challenge outcome (pass versus fail) at 5 years	Ara h 1, 2, 3, and 9-sIgE at 12 months	Accuracy: 83 %, Sensitivity: 91 %, Specificity: 76 %	Accuracy: 77.9 %, Sensitivity: 75.3 %, Specificity: 83.3 %
Gryak et al., 2024[11]	Peanut	LUCCK, Naïve Bayes, and SVM	OFC challenge outcome (pass versus fail)	Demographic, SPT wheal and flare size, total and peanut-sIgE, and Ara h 1, 2, 3, 8, and 9 levels	Accuracy: 0.987, Sensitivity: 0.986, Specificity: 1, AUROC: 0.993, PPV: 1, NPV: 0.9, F1-score: 0.993	Accuracy: 0.935, Sensitivity: 0.763, Specificity: 0.98, AUROC: 0.871, PPV: 0.906, NPV: 0.943, F1-score: 0.829
Srisuwatchari et al., 2024[12]	Wheat	Random forest	OFC challenge outcome (pass versus fail)	Wheat epitope-sIgE	Sensitivity: 0.834, Specificity: 0.884, AUROC: 0.908	Sensitivity: 0.759, Specificity: 0.905, AUROC: 0.908
Suprun et al., 2024[18]	Peanut	Elastic net (glmnet)	SU 12 months after cessation of OIT or Sustained high threshold with no cessation of allergen intake	Age, total IgE, peanut sIgE, peanut epitope-sIgE	Accuracy: 94 %, Sensitivity: 1.0, Specificity: 0.91, AUROC: 0.97	not available
Hendrickx et al., 2025[25]	Milk	Random forest	Cow milk allergy outgrowth at 12 months	Clinical information, proteomic, metabolomic, and metagenomic data	Mean AUROC: 0.868	not available
Özçam et al., 2025[26]	Peanut	Logistic regression and random forest	OIT failure (no remission)	Profile of five gut metabolite bile acids	AUROC: 0.712	not available

OFC, oral food challenge; OIT, oral immunotherapy; LUCCK, Learning using Concave and Convex Kernels; NPV, negative predictive value; PPV, positive predictive value; sIgE, specific-IgE; SPT, skin prick test; SU, sustained unresponsiveness; SVM, support vector machine

outperformed seven state-of-the-art comparators across multiple benchmarks designed to simulate real-world scenarios[4]. The same team has contributed to dust mite allergen characterisation by sequencing the genome of Dermatophagoides farinae - one of the most clinically significant indoor aeroallergens globally - and identifying novel allergens, including Der f 24, thereby establishing a molecular framework for more precise allergen-specific diagnostics and immunotherapy[5]. Illustrating this translational potential, CUHK researchers systematically characterised parvalbumin - the major heat-stable allergen responsible for most IgE-mediated fish reactions - across Asian carp genomes, identifying nine homologs in grass carp alone[6]. Clinical validation revealed that IgE reactivity to the grass carp-specific isoform, Cten i 1, exceeded that of cod and salmon parvalbumins in Hong Kong children, establishing it as the dominant local fish allergen[7]. This bench-to-bedside trajectory demonstrates how genomic discovery can directly yield population-specific allergenic markers, enabling more precise component-resolved diagnostics in communities where freshwater fish consumption is high. Collectively, these advances underscore the region-specific and context-dependent nature of allergen research, and highlight the critical role of foundational molecular work in refining next-generation diagnostic strategies.

PREDICTING ALLERGIC STATUS: EARLY RISK STRATIFICATION

A key application of AI in food allergy is the early prediction of allergic status by integrating routine clinical and demographic data to probabilistically classify children into risk groups before food-allergic symptoms. Birth cohort studies have shown that early-life biomarkers, including skin-barrier lipids and cytokine signatures, can predict later food allergy outcomes, supporting the use of longitudinal biomarker-based risk stratification before clinical disease emerges[8]. EMR-based models have demonstrated superior sensitivity and positive predictive value over family history alone in stratifying infants at risk of peanut allergy[9]. At the molecular level, Suprun et al. showed that peanut component-specific IgE levels (Ara h 1, 2, and 3) at age 2 predicted OFC-confirmed allergic status at age 4 using a random forest model (AUROC 0.87; n=45, CoFAR2)[8], findings corroborated by Grinek et al., who achieved 83 % accuracy on the LEAP dataset and an AUROC of 0.85 on 90 CoFAR2 patients using epitope-specific IgE profiles at 12 months[10]. Unlike conventional approaches relying on single biomarker thresholds, machine learning models can synthesise

multiple variables simultaneously, generating continuous risk scores that better capture the biological heterogeneity of FA. Collectively, these models enable earlier identification of high-risk infants, facilitating timely referral and targeted interventions - which carry the greatest benefit when started early in life.

PREDICTING ORAL FOOD CHALLENGE OUTCOMES

Beyond early risk stratification, AI has shown considerable promise in predicting oral food challenge (OFC) outcomes - a clinically significant application given that OFCs, while the diagnostic gold standard for food allergy, carry inherent risk through direct allergen exposure. Machine learning models trained on routinely collected data - allergen-specific IgE, total IgE, and skin prick test (SPT) wheal and flare measurements - have achieved consistently high predictive accuracy across multiple allergens and independent cohorts. Gryak et al. achieved an AUROC of 0.997 predicting peanut OFC outcomes on the LEAP dataset, with external validation on the IMPACT study yielding an AUROC of 0.871[11]. Strong performance has similarly been reported for wheat (AUROC 0.908, externally validated)[12], sesame (PPV 96%, NPV 98%)[13], and egg (AUROC 0.83)[14]. Notably, these models rely exclusively on biomarkers and clinical measurements already obtained during routine allergy workup, requiring no additional investigations. Collectively, these studies demonstrate that AI can meaningfully support clinicians in stratifying OFC risk, identifying patients unlikely to tolerate challenge, and reducing adverse reactions during diagnostic workup - ultimately offering a safer, data-driven adjunct to conventional allergy assessment.

PERSONALISED TREATMENT DELIVERY

Oral immunotherapy (OIT) has emerged as a proactive treatment strategy for food allergy, with the ultimate goal of achieving sustained unresponsiveness (SU) - maintained allergen tolerance following prolonged avoidance[15]. AI is increasingly transforming OIT from a protocol-driven intervention into a dynamic, data-driven process spanning the full treatment trajectory. At the induction stage, AI-driven platforms integrate allergen-specific IgE, IgE/IgG4 ratios, SPT results, and prior reaction history to assign individualised starting doses and escalation steps, reducing the risk of serious reactions during allergen exposure. Notably, an AI-assisted OIT protocol applied to a cow's milk anaphylaxis cohort achieved 100 % remission in 214 children with low rates of epinephrine-requiring reactions, demonstrating that data-driven dose titration can meaningfully improve both safety and efficacy[16]. During maintenance, AI models continuously recalibrate risk scores and adjust dosing frequency and monitoring intensity based on evolving immunological parameters[16]. At the outcome level, machine learning models trained on epitope-specific IgE profiles have distinguished patients achieving SU from those reaching only desensitisation - Suárez-Fariñas et al. predicting milk OIT outcomes with an AUROC of 0.95[17], and Suprun et al. achieving an AUROC of 0.97 for peanut SU prediction from the POISED trial[18]. Beyond OIT, AI holds further promise in guiding biologic selection - such as anti-IgE or anti-IL-4/13 therapy - in complex multi-allergic children by integrating biomarker and clinical phenotype data[19]. Collectively, these advances position AI as an integral tool in personalising immunotherapy delivery, optimising long-term remission, and supporting shared decision-making between clinicians and families.

WEARABLES AND POINT-OF-CARE DEVICES

Emerging wearable technologies and portable allergen-detection devices are beginning to shift food allergy care from reactive, episode-driven management toward continuous real-time monitoring - a development of particular relevance in paediatric and community settings. The AllergE patch continuously monitors IgE-related biomarkers via microneedles, detecting rising allergic activity before overt symptoms emerge[20], while devices such as Anaphero aim to identify early anaphylaxis signatures through wrist-worn physiological sensors[21]. At the point of use, portable tools such as Allergen Alert and Allergy Amulet enable rapid, lab-grade allergen detection in restaurants, schools, and social settings where laboratory testing is impractical[22]. Crucially, the integration of these platforms with AI-driven risk-scoring algorithms could enable a truly continuous care model - where real-time sensor data dynamically informs risk thresholds, emergency-response prompts, and treatment adjustments between clinic visits, transforming FA management from episodic to proactive.

CONCLUSION & FUTURE DIRECTION

Despite encouraging progress, the application of AI in paediatric food allergy remains in its early stages and is subject to important methodological limitations. Most existing models have been trained on predominantly Western cohorts - such as the U.K.-based LEAP trial - limiting their generalisability to Asian populations, where distinct demographic, dietary, and immunological factors may substantially influence model performance. Sample sizes across studies have generally been small, and discrepancies between validation cohort metrics highlight the risk of overfitting and poor cross-cohort transferability. Current findings should therefore be regarded as proof-of-concept rather than practice-ready tools; stringent large-scale, multi-ethnic external validation is an essential prerequisite before clinical adoption. Looking ahead, significant opportunities exist to advance the field through integration of multi-omics data - including proteomics, genomics, and microbiome profiling - alongside more sophisticated architectures such as deep learning and large language models. Greater transparency and reproducibility in model development and reporting will be equally critical. If these challenges are addressed, AI holds considerable potential to complement clinical decision-making, improve diagnostic precision, personalise treatment, and ultimately alleviate the growing burden of paediatric food allergy on patients, families, and healthcare systems alike.

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Artificial Intelligence in Dementia: Advances in Retinal Imaging and Magnetic Resonance Imaging

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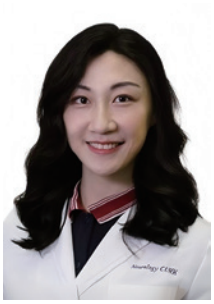

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INTRODUCTION

Dementia has emerged as one of the most significant health challenges of the 21st century. With ageing populations worldwide, the number of people living with dementia is projected to triple by 2050, making it a critical public health priority[1,2]. It has been projected that the number of people with dementia in Hong Kong will increase to approximately 300,000 over the next two decades[3]. For years before symptoms appear, Alzheimer's disease (AD) and related dementias undergo a prolonged preclinical phase during which pathological changes accumulate insidiously, presenting a critical opportunity for early intervention[4]. Yet early detection is hampered by practical limitations of existing diagnostic tools. CSF assays and amyloid PET require lumbar punctures and radiotracer exposure, respectively, restricting their use to specialised centres. Blood-based biomarkers, while promising, are still being validated for widespread clinical adoption. It is critical to develop non-invasive, scalable, and cost-effective screening strategies capable of identifying at-risk individuals.

With recent technological advances, artificial intelligence (AI) has demonstrated remarkable value in image analysis for disease early diagnosis and prognostic monitoring due to its ability to detect subtle pathophysiological changes that are invisible to human observers. This capability enables quantitative, consistent assessments with enhanced accuracy while facilitating large-scale population screening without the variability associated with human interpretation. In the context of dementia, two imaging modalities have shown particular promise: retinal imaging, owing to the retina's unique accessibility as a direct extension of the central nervous system, and magnetic resonance imaging (MRI), which provides direct visualisation of brain atrophy, white matter pathology, and connectivity. This review examines the state of the art in both domains, highlighting their complementary strengths and limitations, as well as the growing potential for combining these approaches into integrated AI diagnostic systems.

CURRENT AI TECHNIQUES IN DEMENTIA

The overarching goal of AI is to create machines that can perform tasks that typically require human intelligence, which may include reasoning, problem solving and decision making. As an approach within AI, machine learning (ML) encompasses various algorithms that can learn and improve from data to identify patterns and make predictions or decisions based on those patterns. Support vector machines (SVMs) were among the earliest ML methods applied to neuroimaging for dementia classification and remain a benchmark approach for binary classification tasks by seeking the optimal hyperplane that best differentiates outcomes in the feature space[5]. Decision trees provide the importance of each feature by splitting the data into subgroups like tree branches, following preset decision rules. Random forest (RF) methods, leveraging ensembles of decision trees, offer robustness against overfitting and provide natural feature importance estimates, which is a valuable property for neuroimaging biomarker discovery. Traditional MRI-based machine learning analysis has produced good diagnostic performance, offering 75-85 % accuracy for discriminating AD from healthy control (HC) and mild cognitive impairment (MCI) to AD converters vs. non-converters[6].

Deep learning, a subset of ML methodologies, has demonstrated superior performance through its capacity for autonomous hierarchical feature extraction. Convolutional neural networks (CNNs) and their advanced variants (e.g., ResNet, EfficientNet architectures, 3D CNNs) consistently achieve enhanced accuracy by automatically learning multi-level feature representations directly from raw image data. This end-to-end learning paradigm substantially reduces the dependency on manual feature engineering, enabling more robust and generalisable pattern recognition capabilities[6,7]. Recurrent neural networks (RNNs), particularly long short-term memory (LSTM) networks, are designed to model sequential dependencies and are therefore well-suited to analysing longitudinal image changes over time[8]. Vision transformers (ViTs) are a newer deep learning architecture that applies self-attention to image patches, enabling global pattern

modelling, particularly suitable for neuroimaging applications where dementia manifests as network-level connectivity disruptions rather than isolated atrophy[9]. Recent studies have demonstrated that deep learning approaches achieve remarkable diagnostic accuracy, with MRI and retinal imaging-based models capable of reaching classification performance exceeding 80 %-90 %[6,10].

AI IN RETINAL IMAGING FOR DEMENTIA

The Retina as a Neurovascular Window

The retina shares embryological origin with the brain and maintains direct anatomical continuity with the central nervous system via the optic nerve[11]. Complementing this neural link, the retina receives vascular supply from the central retinal artery - a branch of the ophthalmic artery that stems from the internal carotid circulation. This relationship is increasingly recognised as clinically informative: retinal changes in AD include thinning of the retinal nerve fibre layer (RNFL) and ganglion cell layer (GCL), reduced vascular density, enlargement of the foveal avascular zone[12]. Through this combined neurovascular architecture, the retina functions as an optically accessible window for non-invasive visualisation of central nervous system components, presenting unique opportunities for real-time monitoring of neurological structure, function, and pathological alterations in neurodegeneration.

Colour Fundus Photography-based Models for Dementia

Digital colour fundus photography (CFP) represents the most accessible and widely utilised retinal imaging modalities, providing comprehensive visualisation of the optic disc, macula, retinal architecture, and vascular network[13]. In a landmark study published in The Lancet Digital Health (2022), a Chinese University of Hong Kong (CUHK)-led international team developed the world's first AI model capable of detecting AD exclusively through CFP. The deep learning framework was trained and validated using approximately 13,000 fundus photographs from 648 clinically confirmed AD patients and 3,240 cognitively intact controls, encompassing multi-ethnic, multinational cohorts across Asia. Employing a CNN-based deep learning architecture, the model demonstrated robust diagnostic performance with 84 % accuracy, 93 % sensitivity, and 82 % specificity during internal validation. Cross-population external validation across diverse geographic regions yielded consistent accuracies ranging from 80-92 %. Notably, the model maintained diagnostic reliability even in the presence of concurrent ocular pathologies, including age-related macular degeneration and glaucoma[10].

Building upon this validated model, the research team developed a comprehensive digital health platform termed "i-Cog Brain Health", incorporating a user interface, information management system, and automated image quality control algorithms for retinal photograph analysis. In community-based studies involving non-demented older adults, the i-Cog Brain Health system demonstrated significant associations with older age and wider venular branching width, suggesting its potential utility for early-stage retinal feature differentiation and dementia risk stratification[14]. Real-world validation demonstrated that subjects with positive i-Cog Brain Health results had an almost 3-fold increased risk of developing symptomatic AD compared to those with negative results. Among cognitively normal participants, positive cases were characterised by significantly older age, lower baseline Montreal Cognitive Assessment-5 (MoCA-5) scores, reduced educational attainment, lower socioeconomic status, and decreased lifestyle risk factor burden. Notably, positive i-Cog Brain Health results served as an effective motivational tool for lifestyle modification, with participants showing improved adherence to health recommendations following nurse-led lifestyle education interventions. These findings demonstrate that i-Cog Brain Health enables practical community-based screening protocols and facilitates targeted brain health management strategies for at-risk populations (Fig. 1).

Employing different models and focusing on different retinal features can improve model performance or enable their application across different types of cognitive impairment. A prospective cohort study of 491 participants demonstrated that deep learning-based automated retinal vessel measurements predicted cognitive decline, with narrower arteriolar and wider venular calibres associated with increased risk, establishing retinal vascular analysis as a potential non-invasive neurocognitive biomarker[15]. A recent study developed two distinct deep learning architectures for AD detection from CFP combining vessel segmentation maps - ADVAS (U-Net-based vessel segmentation model) and ADRET (bidirectional encoder representations from transformers-style self-supervised CNN) - with ADRET demonstrating significantly superior performance across U.K. Biobank and institutional datasets (98.3 % vs 77.2 % accuracy in U.K. Biobank, 98.9 % vs 94.2 % in institutional data), while attention heatmap analysis revealed that AD classification decisions were primarily based on regions surrounding small retinal vascular branches[16]. Another single-centre cross-sectional study also showed the ability of CFP-based deep learning model in detecting MCI in patients with coronary artery disease, with an area under curve (AUC) of 83.2 % and 76.4 % for Mini-Mental State Examination (MMSE) and MoCA-based classifications, respectively, demonstrating the potential of retinal imaging as a non-invasive screening tool for cognitive decline in cardiovascular populations[17].

Optical Coherence Tomography-based Models for Dementia

Optical coherence tomography (OCT) provides high-resolution quantification of retinal structure, enabling precise and reproducible measurement of structural neuroaxonal loss across disease stages. OCT technology exists in two main generations: Time-Domain OCT (TD OCT), the older first-generation technology with slower scanning and lower resolution (~10 μm), and Spectral-Domain OCT (SD OCT), the newer second-generation technology that provides faster scanning,

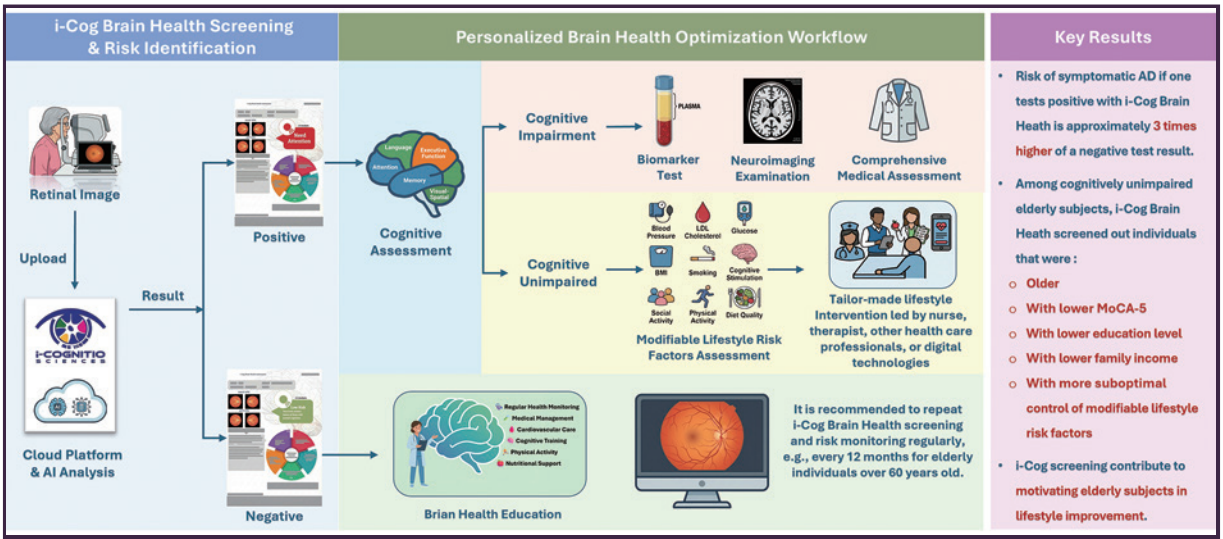

Fig. 1: i-Cog Brain Health Screening and Personalised Optimisation Workflow. This diagram illustrates a comprehensive AI-powered brain health assessment system utilising retinal imaging as the primary screening modality. The workflow begins with retinal image capture and upload to a cloud-based AI analysis platform (left panel, blue). For those who have postive i-Cog results, following cognitive assessment, the system bifurcates into two personalised pathways: individuals with cognitive impairment are recommended for comprehensive evaluation including biomarker testing, neuroimaging examination, and medical assessment. Meanwhile, cognitively unimpaired individuals receive modifiable lifestyle risk factor assessment and tailored lifestyle interventions delivered by healthcare professionals or digital technologies. For those who have negative i-Cog results, the subjects should also receive brain heath education. The system recommends regular re-screening (e.g., every 12 months for individuals over 60 years old). Key clinical outcomes (right panel, pink) demonstrate that positive i-Cog Brain Health screening results indicate approximately 3-fold higher risk for symptomatic Alzheimer's disease compared to negative results. Among cognitively unimpaired elderly subjects, the screening successfully identified high-risk individuals who were older, had lower MoCA-5 scores, lower education levels, lower family income, and more suboptimal modifiable lifestyle risk factors. The i-Cog screening system also contributed to motivating lifestyle improvement initiatives among elderly participants.(Personal collection)

higher resolution (~5 μm), and significantly improved image quality for more accurate retinal analysis[18]. The CUHK team developed an SD OCT based ensemble deep learning model that achieved an AUC of 94.3 % for dementia detection in internal validation. When applied to external validation cohorts, the model showed promising performance in early detection of amyloid-positive MCI, achieving an AUC of approximately 79 %[19]. Another ensemble trilateral deep learning model using SD OCT demonstrated great diagnostic ability for AD and MCI detection in both Asian (AUC = 0.91) and White (AUC = 0.84) populations[20]. A systematic review and meta-analysis of 30 studies demonstrated that AD is consistently associated with widespread retinal structural thinning detectable by SD OCT, including significant reductions in GCL, macular volume and thickness, RNFL, and choroidal thickness compared to healthy controls[21]. This consistent pattern of retinal and choroidal atrophy across multiple anatomical structures reflects the neurodegenerative processes characteristic of AD pathology.

OCT angiography (OCTA) extends this capability to the microvasculature, generating depth-resolved maps of the superficial and deep capillary plexuses and the deep vascular complex. The Eye-AD framework exemplifies the state of the art in OCTA-based AI. Trained on 5,751 images from 1,671 participants, the model employed a multi-stage CNN pipeline applied to quantitative vessel density maps derived from OCTA, achieving an area under the AUC of up to 95 % for MCI and early-onset AD from cognitively normal controls[22]. The derived model outperformed conventional ophthalmological biomarkers assessed in the same cohort, including manually graded RNFL thickness and vascular density indices.

Limitations of Retinal-based Models

While OCT and OCTA technologies demonstrate considerable promise as non-invasive biomarkers for AD detection, their clinical implementation faces certain limitations that currently restrict their diagnostic utility. Technical variability across different OCT platforms, scanning protocols, and image processing algorithms introduces measurement inconsistencies that are particularly problematic when detecting the subtle retinal changes characteristic of AD. The accuracy of these measurements remains heavily dependent on operator expertise and patient cooperation, with factors such as eye movement artefacts, media opacities, and age-related ocular conditions potentially compromising image quality and reliability[23]. Perhaps most critically, the structural and vascular alterations identified by OCT/OCTA lack specificity for a specific subtype of dementia, as similar retinal changes have been documented across various neurodegenerative disorders including Parkinson's disease[24]. This limitation, combined with insufficient comparative studies between different dementia subtypes, suggests that current OCT-based retinal biomarkers should be viewed as indicators of general neurodegeneration rather than disease-specific diagnostic tools. Consequently, realising the full potential of OCT technology for dementia detection

will likely require integration with complementary biomarkers and continued technological refinements to enhance both sensitivity and diagnostic specificity.

AI IN MRI FOR DEMENTIA

Structural MRI-based Models for Dementia

Structural MRI, particularly T1-weighted sequences, has been the most widely used neuroimaging modality in AI-based dementia research. In clinical practice, brain structural MRI is commonly the first-line imaging modality for the evaluation of subjects presenting with cognitive decline. Furthermore, as one of the critical steps, evaluation of small vessel disease with MRI affects the sequential application of the potential disease-modifying agent (i.e., anti-amyloid monoclonal antibody) for prodromal AD[25]. A characteristic pattern of neurodegeneration (N+) can be captured in vivo by MRI years before symptoms appear. Decrease in hippocampal volume (HV) is the most well-established structural biomarker for AD, particularly for early diagnosis[26,27]. In addition, the rate of change in several structural measures, including that of the whole brain, entorhinal cortex[26], parietal lobe (in particular the praecuneus and posterior cingulate cortex)[28,29], and the frontal lobe, have all been shown to correlate with cognitive decline[30].

When applying ML algorithms to structural MRI for classification between AD and HC, the accuracy varies widely depending on the selected methods[31-33]. In predicting MCI to AD converter, the MRI-based AI-derived model achieved around 70-80 % accuracy[34]. The AD-RAI, a machine learning-derived MRI-based neurodegeneration biomarker of AD, was generated using AccuBrain® from T1 MRI volumetric measurements, measuring similarity of brain atrophy patterns with AD patients on a 0-100 % scale (higher scores indicating more severe atrophy). After automated preprocessing (noise reduction, bias correction, intensity normalisation), a CNN-based model performed brain segmentation, calculating absolute and relative volumes (% of intracranial volume). AD-RAI was then derived using SVM analysis of AD-relevant volumetric features from subcortical structures, ventricles, and cortical regions. The entire cloud-based AccuBrain® pipeline automatically processed each subject within 10 minutes and showing comparable performance with FreeSurfer and other automated segmentation software[35]. AD-RAI showed an AUC of 93 % in differentiating AD from CU,[36] and also showed superior performance compared to traditional imaging measures, such as HV, and blood-based neurodegeneration biomarkers (e.g., neurofilament light chain) in predicting cognitive decline in early AD[37,38].

Functional and Diffusion MRI -based Models for Dementia

Resting-state functional MRI (rs-fMRI) offers complementary information by capturing disruptions in functional network connectivity, particularly within the default mode network (DMN), which is consistently implicated in early AD. Deep learning models applied to rs-fMRI connectivity matrices or time-series data have demonstrated strong discriminative capacity for AD and HC[39,40], though the sensitivity of fMRI data to motion artefacts, preprocessing choices, and scanner differences represents a significant methodological challenge[41]. The fMRI-based AI model also showed great ability in cognitive staging. A longitudinal study using rs-fMRI in 138 subjects achieved Alzheimer's stages classification including CN, SMC, EMCI, MCI, LMCI, and AD with up to 98 % accuracy and 97.9 % average accuracy using a fine-tuned ResNet-18 algorithm[42]. Another meta-analysis including 23 studies, showed over 95 % diagnostic accuracy in the multi-class classification tasks ranging from HC to late MCI[43].

Diffusion tensor imaging (DTI) captures microstructural white-matter integrity, with fractional anisotropy (FA) and mean diffusivity (MD) changes in the corpus callosum, fornix, cingulum, hippocampal and medial temporal tracts serving as established markers of AD-related neurodegeneration and vascular injury[44,45]. A recent study combining MRI with DTI in a hybrid deep learning framework achieved a mean average precision of 96.7 % for early AD detection[46], underscoring the value of integrating structural and microstructural information.

Limitation and Future Direction of MRI-based Models

Despite remarkable advances, AI neuroimaging for dementia faces several technical barriers. First, MRI acquisition protocols vary substantially across studies, encompassing differences in magnetic field strength, pulse sequence parameters, and scanner manufacturers, which introduce systematic non-biological variation that can significantly compromise model performance when applied to datasets from different sources than the training data. Second, generalisability remains a fundamental limitation, as models trained on well-curated research cohorts such as the Alzheimer's Disease Neuroimaging Initiative (ADNI) - characterised by carefully selected subjects with minimal co-pathology - often fail to transfer effectively to clinical populations with mixed pathologies, atypical presentations, and multiple comorbidities[33]. Third, the interpretability challenge posed by the "black box" nature of deep neural networks limits both clinical adoption and scientific understanding, since while post-hoc explanation methods such as Gradient-weighted Class Activation Mapping (Grad-CAM)[47], SHapley Additive exPlanations (SHAP)[48], and Local Interpretable Model-agnostic Explanations (LIME)[49] can generate visual saliency maps and feature attribution scores, these explanations represent only approximations that may not accurately reflect the model's actual decision-making processes.

The clinical translation of MRI-based AI requires validation across diverse scanner platforms and imaging protocols to ensure robust performance in real-world settings. While the ADNI initiative has provided valuable retrospective validation data, prospective real-world studies are essential to capture the full spectrum of clinical dementia presentations encountered in routine practice. Additionally, future developments

should focus on creating a tiered, multimodal AI diagnostic framework. Initial screening could utilise accessible modalities like retinal imaging and blood biomarkers, with positive cases proceeding to MRI-based analysis. This hierarchical approach would integrate MRI data with clinical information (cognitive scores, medical history, demographics) to provide comprehensive risk stratification. Such tiered systems could optimise healthcare resources by reserving expensive neuroimaging for high-risk individuals identified through preliminary screening, while providing increasingly precise diagnostic confidence as additional data layers are incorporated. Standardised protocols and uncertainty quantification across all modalities will be essential for safe clinical deployment of these integrated AI diagnostic pipelines.

CONCLUSION

This review demonstrates that AI-driven neuroimaging approaches, encompassing both retinal imaging and brain MRI, represent a paradigm shift toward accessible, non-invasive dementia screening and early detection. Retinal imaging, particularly through CFP and OCT-based models, allows for large-scale screening programmes, with validated frameworks such as i-Cog Brain Health successfully implemented in real-world settings and showing significant associations with dementia risk. Meanwhile, MRI-based AI models provide detailed brain structure analysis, with structural, functional, and diffusion imaging approaches achieving high diagnostic accuracy across multiple cognitive stages. However, several issues need be addressed when widespread clinical adoption is being considered: technical variability across imaging platforms introduces systematic biases that compromise model generalisability; current models trained mainly on research cohorts may not work effectively in diverse clinical populations; and the difficulty of understanding how AI models make decisions remains a barrier to clinical acceptance. By combining different imaging modalities with AI, we can develop more accurate and accessible tools for early dementia detection, potentially improving outcomes for patients across diverse healthcare settings. Success will depend on addressing current technical limitations while encouraging collaboration between AI researchers, clinicians, and health authorities to ensure safe and effective implementation of these technologies.

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Radiology Quiz

Radiology Quiz

Dr Andrew Man-kwun LI

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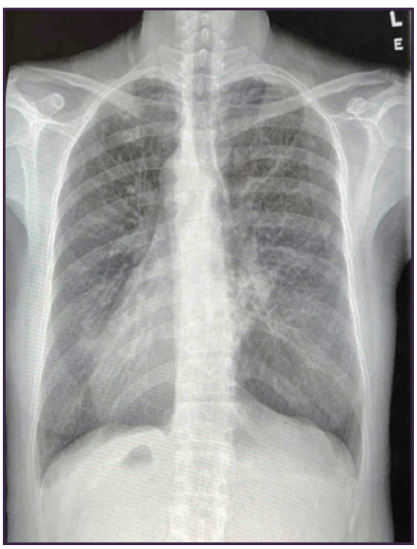
Dr Andrew Man-kwun LI



Clinical history

A young adult patient who has suffered from recurrent respiratory infections since an early age.

Questions

1. What are the abnormalities on this radiograph?
2. What is the likely diagnosis?
3. What further workup is required for this patient?

(See P.41 for answers)

kisunla® (donanemab)

For your patients with early symptomatic Alzheimer's disease (AD) and confirmed AD pathology[1]

WITH THE POWER TO SLOW DECLINE IN AD, YOU CAN HELP MAKE MOMENTS LAST LONGER[1]

Kisunla® slowed cognitive and functional decline in patients with MCI or mild dementia due to AD.[1]

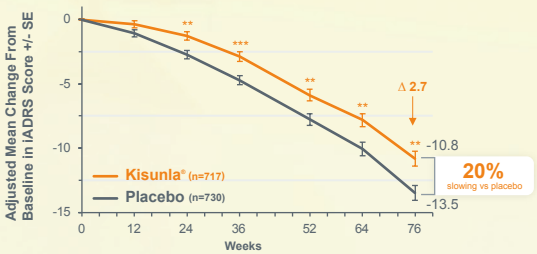
KISUNLA® is indicated for the treatment of patients with Mild Cognitive Impairment (MCI) due to Alzheimer's disease and Mild Alzheimer's dementia (Early Symptomatic Alzheimer's disease) that are apolipoprotein E ε4 (ApoE

Kisunla® gives you the power to help slow cognitive and functional decline in patients with early symptomatic Alzheimer's disease (AD)[1]

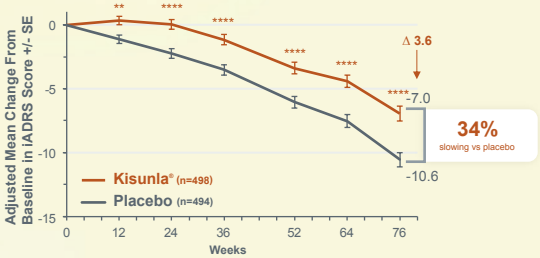
Significant Slowing of Cognitive and Functional Decline with Kisunla® (Non-Carriers and Heterozygotes)[1-3]

iADRS CHANGE FROM BASELINE THROUGH 76 WEEKS

Overall indicated population[1,2†]



Low-medium tau indicated population[1,3†]



TRAILBLAZER-ALZ 2 trial design

In this study, 1736 patients were randomized 1:1 to receive 700 mg of Kisunla® every 4 weeks for the first 3 doses, and then 1400 mg every 4 weeks via intravenous infusion (N=860) or placebo (N = 876) for a total of up to 72 weeks. The primary efficacy endpoint was change in the integrated Alzheimer's Disease Scale (iADRS) score from baseline to 76 weeks. Amyloid clearance* was assessed with amyloid PET scans at 24, 52, and 76 weeks, discontinuation, or study completion (76 weeks). ARIA-monitoring MRIs were performed before infusions 1, 2, 3, 4, and 7.[1,4]

*Cleared defined as when patients reach amyloid levels considered negative for amyloid pathology. <24.1 Centiloids equaled a negative amyloid PET scan. If the amyloid plaque level was <11 Centiloids on a single PET scan or 11 to <25 Centiloids on 2 consecutive PET scans, the patient was eligible to be switched to placebo.[1]

Key Kisunla® Takeaways[1-8]

As measured compared to placebo TRAILBLAZER-ALZ 2 at 76 weeks:[1-3,5-7]

- **Significant slowing of cognitive and functional decline in the indicated population**
- **38% reduced risk of progressing to the next stage of disease and of 48% reduced risk of progressing to moderate dementia in the indicated population**

- **Potential to stop dosing upon removal of amyloid plaques to minimal levels[1†]**
- **Once-monthly 30-minute infusion[1]**

As measured in the gradual-titration arm compared to original dosing in TRAILBLAZER-ALZ 6:

- **Reduced frequency of ARIA-E[8]**

Kisunla®, like other amyloid-targeting therapies, can cause ARIA, which is usually asymptomatic, though rarely serious and life-threatening events can occur. ARIA can be fatal.[1,4]
In TRAILBLAZER-ALZ 2, the most frequently reported adverse reactions in the indicated population were ARIA-E, ARIA-H, and headache.[1]

†In the Phase 3 clinical trial, dosing was continued or stopped in response to observed effects on amyloid-PET imaging.[4]

ARIA=Amyloid-related imaging abnormalities; iADRS=integrated Alzheimer's Disease Rating Scale; IV=intravenous; LS=least squares; MCI=mild cognitive impairment; MRI=magnetic resonance imaging; PET=positron emission

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A Review of Using Artificial Intelligence in Chinese Medicine

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Chinese Medicine (CM) is widely accepted in its integration with Western Medicine in providing treatment and promoting health[1,2]. CM possesses its unique philosophical framework with multi-dimensions and is rather complex in conceptualisation and treatment formulation. The rationales are difficult to stipulate briefly to facilitate communication, creating a barrier to replication. With the advancement of Artificial Intelligence (AI) in handling massive clinical data, ancient books and clinical experiences, knowledge consolidation and modernisation of CM become feasible.

AI has been widely used in health care. The first scoping review of AI in elderly healthcare summarised 105 studies from 2000 to 2022, covering the use of robots, exoskeleton devices, AI-enabled health smart applications, wearables, voice-activated intelligent home control, risk prevention and virtual reality[3]. That focused on physical treatment, cognitive rehabilitation, emotional support, socialisation and supervision. Although it offered comprehensive references for various AI applications, it did not cover the scope of CM. Hence, a review of AI applications in CM was conducted.

With extensive searches of PubMed and the Cochrane database, four studies were found that summarised the recent applications of AI in CM, improving the following five areas: diagnostic precision, treatments, data analysis and drug discovery, education and management[4-7].

ENHANCEMENT OF DIAGNOSTIC PRECISION

AI offer objective multi-faceted screening information and benefits the four CM diagnostic methodologies, particularly tongue inspection, pulse palpation, odour, facial and lip colour diagnosis.

The use of health screening using image recognition technology in AI for tongue inspection, and correlation of the tongue features with internal organ functions, has been developed for years. The application of machine learning and deep learning algorithms to tongue size, coating and sublingual veins has been a major research focus[5,8].

Images of pulse waveforms during palpation have been extensively studied using machine learning algorithms and more complex hierarchical multi-layer networks, such as convolutional neural network for mining local characteristics and images. Correlation of diagnosis with colorectal cancer, hypertension, cardiovascular disease and diabetes mellitus have been established. Different methodologies have been used, including adaptive pressure-sensing pulse waves platforms, thin-film piezoelectric sensors, multipoint composite sensing systems, bionic robots, photoelectric volumetric wave tracing methods in pattern recognition[7]. An ongoing study on the correlation between CM pulse patterns and body constitution types in healthy human subjects is being led by a research team at the University of Hong Kong[9].

Furthermore, facial colour features, lip colour diagnosis and odour monitoring system are emerging areas of exploration[7]. The emerging TCM auscultation system, which identifies patient speech and sound using frequency spectrum analysis and cough sounds using digital sonography requires further research[10]. A traditional Chinese medicine five-tone intelligent diagnosis based on the Chinese Five Elements and related music therapy has recently been developed[11].

In the future, a multi-modal integrated analysis model that combines knowledge bases, images, electrophysiological pulse waveforms and test results could definitely offer more comprehensive, objective and precise CM diagnosis for patients.

APPLICATION IN TREATMENTS

AI technologies of research methodologies such as text and data mining, item analysis, decision analysis, clustering analysis and formula-syndrome association studies could uncover CM knowledge to promote evidence based-practice of different CM treatment modalities, i.e. Chinese herbal medicine, acupuncture, massage, moxibustion, food therapy and health qigong practice.

Chinese herbal therapy is the most widely used CM treatment, employing plant, animal and mineral substances. CM practitioners often use several substances in a herbal formula to achieve therapeutic effect. With AI technology using machine learning algorithms and knowledge-augmented learning models (e.g., knowledge graph, ontology reasoning, causal relationships and neural networks as reasoning layers), the development of an intellectual consultation system becomes feasible. The study of multi-modal fusion-driven design of CM intelligent consultation of spleen-stomach disorder, which incorporates historically text-

based medical knowledge and shifts from experiential judgment to data-driven analytical approaches, is an example of such an intelligent consultation system[12].

Recent advances in robot-controlled acupuncture not only offer accurate identification of acupuncture points but also provide stimulation through a robotic arm and automated detection of the deqi phenomenon. Furthermore, the development of robotic-controlled ear acupuncture is also progressing[13]. Meanwhile, the 3D morphable model of a computer supported the development of robotic massage with reference to acupoint location.

The use of augmented reality for rehabilitation is common in the hospital settings of the Hospital Authority in Hong Kong, such as the use of health qigong Baduanjin combined with an e-learning platform and motion sensors to provide feedback to enhance patient learning.

APPLICATION IN DATA ANALYSIS AND DRUG DISCOVERY

With advances in AI, more sophisticated statistical analyses, such as network target navigating analysis and network relationship mining can be adopted to assist knowledge consolidation of CM and to provide evidence-based knowledge translation in modern language[14]. The mechanism of CM can be explored using unsupervised machine learning for cellular functional similarity of compounds in heterogeneous networks as demonstrated in the study of XiaoErFuPi granules[15].

Data validity for analysis is very important in AI model building. A study comparing different databases (e.g., TCMbank, HIT 2.0, TCMID 2.0, SuperTCM, TCMSID, HERB, SymMap, ETCM v2.0, BATMAN-TCM 2.0, LTMTCM etc.) that provide CM prescriptions, herbs, chemical ingredients, targets and diseases was used. The access paths for these data are available and serve as good references for future studies[4]. With public databases available for network pharmacology analysis, the 'multi-component, multi-target, multi-pathway' approach can be handled more easily[16].

Researchers have used cycberpharmacology to accelerate drug screening for the best drug candidates. Researchers used the CM Systematic Pharmacology platform and CM integrated database to summarise core formulas and medicines. Then, targets were searched using related databases such as DisGeNET and GeneCards, and PyRx software, and before verifying the affinity between target drugs and target proteins using molecular docking techniques. Researchers also performed natural language processing on ancient Chinese medical texts and medical reports to obtain multidimensional herb feature vectors and side-effect reports for subsequent therapeutic efficacy prediction of target herbal medicine candidates[6]. The AI-assisted drug virtual screening can be divided into structured-based, ligand-based and relationship-based modelling to identify molecular docking, structure-based pharmacophores, ligand-based pharmacophores and molecular dynamics using unsupervised hierarchical clustering[17]. In brief, AI is a very good tool for drug discovery.

APPLICATION IN EDUCATION

Large language models (LLMs) have been used to model CM dialogues on real-world datasets. With the prevalence of LLMs in handling vast amounts of data, especially supporting natural language processing tasks (e.g., ChatGPT, Deepseek, Poe, Qwen, ERINE Bot and Microsoft Copilot), public access for knowledge sharing and interpretation of herbal formulas and differential diagnoses has become easily available. The convenience of using interactive AI for CM by the public will become a focus, as well as creating a challenge for the healthcare providers in the future[18]. Similarly, updating the knowledge and technical skills of using AI and modern technologies would be essential for all healthcare providers, especially for advancing clinical service and knowledge consolidation. Development and application of AI in CM is vital for future CM modernisation[19].

AI technology also facilitates student learning. An acupoint health care system with real-time acupoint localisation and visualisation in 3D augmented reality models helps speed up student learning of acupuncture[20]. One Hong Kong example is the development of '3D Acu-Man' at the Hong Kong Museum of Medical Sciences, a modern copper-printed acupuncture model with augmented reality technology and sensors for interactive learning.

Combination with real-world data with integrated Chinese and Western medicine diagnostic systems and medical record databases could help provide comprehensive assessment information to facilitate better patient management.

APPLICATION IN MANAGEMENT

AI can also support risk management through the application of network toxicology in the safety assessment of Chinese medicine[21]. Another practical risk management example is the use of AI through a deep learning-based cloud service system for automatically counting acupuncture needles to alert CM practitioners and enhance acupuncture safety in daily practice[22].

CM promotes nourishing health in normal times and preventing illness recurrence. With the acquisition of large amounts of data, the product lifecycle and stakeholder analysis can be conducted to aid clinical governance for sustainable development and increase resource utilisation efficiency[23].

DISCUSSION

The lack of well-organised, valid data warehouses of CM records remains a critical challenge for AI-assisted CM research. Therefore, standardised knowledge consolidation with evidence-based practice (EBP) to remove noise while retaining precision should be promoted. There is also an emerging need to develop governing principles for the use of AI, protect data security, and avoid misuse of AI technology. In the future, open platforms and the development of self-

help applications using apps with wearable devices could improve quality of life and help manage minor signs and symptoms through over-the-counter drugs or herbal medicine prescriptions. Future systems to monitor patients' conditions using wearables could increase safety and track health progress.

CONCLUSION

CM has been in use for decades because of its effectiveness. With the use of AI, CM treatment regimens can be stipulated more clearly using common language. Knowledge consolidation and transfer can be more easily achieved. In this AI era, the trend and culture of using AI in healthcare is unavoidable. Our healthcare successors in CM should learn AI and further advance Chinese wisdom in a more systematic and effective way. The barrier of information inequality in healthcare could be removed with the help of AI to improve knowledge accessibility for the public. The intent of this article is to interpret Chinese wisdom using AI as an interpreter. However, the importance of doctor-patient communication is definitely irreplaceable. AI contributes to future development but should not replace the vital steps of human touch in healthcare. Future studies using an integrative approach to explore how AI can support the West-and-East healthcare system are worth pursuing.

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35% reduction

in exacerbations requiring hospitalisations and/or ED visits

Nucala, **0.13/year** (n=403) vs. placebo, **0.20/year** (n=401) at Weeks 52-104; RR: 0.65 (95% CI: 0.43, 0.96).[1,2]

MATINEE secondary endpoint;[1,2] results are nominally significant.

NUCALA
mepolizumab

*Hospitalisations/ED visits of any length due to an exacerbation.[2]

• Moderate exacerbations defined as exacerbations (worsening of COPD symptoms) requiring treatment with systemic corticosteroids and/or antibiotics. Severe exacerbations defined as those requiring hospitalisation (≥24 hours) or resulting in death.[1,2] MATINEE: 21% reduction in overall moderate or severe exacerbations at Weeks 52-104 for Nucala, 0.80/year (n=403) vs. placebo, 1.01/year (n=401). RR: 0.79 (95% CI: 0.66, 0.94; p=0.01) primary endpoint.[1,2] Mean rate of exacerbations in previous year in the Nucala population: 2.3.[2] • ICS + LABA + LAMA.[1]

Pivotal Trial Descriptions:[1-3] Two multicentre, randomised, double-blind, trials evaluated Nucala 100 mg SC every 4 weeks vs. placebo, each added to SoC,[3] in patients ≥40 years of age with COPD, a history of exacerbations (≥2 moderate or ≥1 severe) in past year, moderate to very severe airflow limitation,[a] and current/former smoking status.[1] **MATINEE:** 52- to 104-week trial in 804 patients with an EOS phenotype (defined as BEC of ≥300 cells/μL at screening). Patients with a past or present asthma diagnosis were excluded. **METREX:** 52-week trial (N=836); Patients were stratified by BEC with the efficacy population (EOS phenotype, n=462) defined as ≥150 cells/μL at screening or ≥300 cells/μL in past year. There was insufficient data to support the efficacy of NUCALA in patients with BEC <150 cells/μL at screening with no evidence of ≥300 cells/μL in past year. Patients with present asthma diagnosis (smokers/former smokers) and history of asthma (never smokers) were excluded.

• Mean rate of exacerbations in previous year in the Nucala population: MATINEE 2.3; METREX 2.5.[2,4]

BEC, blood eosinophil count; CI, confidence interval; COPD, chronic obstructive pulmonary disease; ED, emergency department; EOS, eosinophilic; ICS, inhaled corticosteroids; LABA, long-acting beta$_2$-agonist; LAMA, long-acting muscarinic antagonist; RR, rate ratio; SOC, standard of care.

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Important Safety Information • Nucala (mepolizumab) 100 mg solution for injection in pre-filled pen **Contraindications:** • Hypersensitivity to the active substance or to any excipients of Nucala solution for injection. **Warnings and Precautions:** • Not to be used to treat acute asthma or COPD exacerbations. Asthma-related or COPD-related adverse symptoms or exacerbations may occur during treatment. • Abrupt discontinuation of corticosteroids after initiation of Nucala therapy is not recommended. • Acute and delayed systemic reactions, including hypersensitivity reactions (e.g. anaphylaxis, urticaria, angioedema, rash, bronchospasm, hypotension), have occurred following administration of Nucala. • In the event of a hypersensitivity reaction, appropriate treatment as clinically indicated should be initiated. • Pre-existing helminth infections should be treated before starting Nucala. • Nucala has not been studied in patients with organ threatening or life-threatening manifestations of EGPA. • Nucala has not been studied in patients with life-threatening manifestations of HES. **Adverse Events:** ***Most commonly reported adverse reactions in:*** • Severe eosinophilic asthma: headache, injection site reactions and back pain • COPD: headache, back pain and arthralgia • CRSwNP: headache and back pain • EGPA: headache, injection site reactions and back pain • HES: headache, urinary tract infection, injection site reactions and pyrexia.

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Beyond the Black Box: Building an AI Safety Net for Paediatric Anaesthesia

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THE CURRENT LANDSCAPE OF ADULT RISK ASSESSMENT

Preoperative patient assessment is a fundamental component of anaesthesia care, serving the ultimate goal of accurately evaluating and predicting perioperative risks to guide clinical management and shared decision-making among clinical teams. To achieve this, the American Society of Anesthesiologists Physical Status (ASA-PS) classification is the most widely used risk assessment tool, valued for its simplicity of use, especially at the bedside. Although it is currently used all over the world as a surgical risk prediction metric, it was actually introduced 80 years ago strictly for statistical purposes and was never intended to predict individual perioperative risk[1]. Because each variable required to "calculate" the ASA-PS lacks strict scientific definitions, the resulting ASA-PS would then rely heavily on subjective clinical intuition, resulting in high interobserver variability. For example, consider a 75-year-old patient with well-controlled hypertension presenting for repair of a fractured neck of femur. By strict ASA-PS criteria, controlled hypertension would result in an ASA II classification for the patient, as age and acute localised trauma are not systemic diseases. However, due to the high anticipated surgical risk and patient frailty, many clinicians will subjectively upgrade this patient to an ASA III. This conflation of physical status with surgical risk highlights exactly why the tool relies on subjective intuition and will result in different clinicians attributing a different ASA-PS to the same patient. So, while the ASA-PS correlates well with population-level mortality, its predictive accuracy for any individual patient is limited, generally yielding Area Under the Curve (AUC) values between 0.69 and 0.777 for mortality within 30 days and major complications[2].

While there are other traditional tools which have been repurposed for perioperative prediction[3] - such as the Revised Cardiac Risk Index (RCRI), APACHE II, and the Charlson Comorbidity Index (CCI) - they face similar constraints, as they require extensive physiological data collection (such as laboratory results, blood gas data or vital signs). In addition to these constraints, such risk assessment tools were actually originally designed for different clinical outcomes, including major cardiac events, mortality after ICU admission, or long-term mortality, rather than specifically being designed for perioperative outcome prediction[2]. To overcome the limitations posed by these models, modern anaesthesia has begun transitioning towards the use of advanced models, such as the Preoperative Score to Predict Postoperative Mortality (POSPOM) and the Universal ACS-NSQIP surgical risk calculator[4]. While these models are able to calculate individualised mortality risk percentages and demonstrate improved accuracy compared to the RCRI or APACHE II, they are clumsy to use and require information input into a separate device with internet access. Other reasons why these calculators have suffered low uptake are the lack of clinical transparency - when doctors do not know how each of the variables contributes to the final prediction, they are less likely to use the tool.

THE PAEDIATRIC PARADIGM: HIGHER STAKES AND PERSISTENT GAPS

While the limitations of traditional scoring apply across all demographics, the stakes are exponentially higher when dealing with children. Thankfully, 30-day in-patient mortality following paediatric surgery is exceedingly rare, but when it does occur, it is a catastrophic event. To standardise risk stratification, paediatric anesthesiologists frequently utilise tailored scoring systems like the Paediatric Risk Assessment (PRaM) score[5] and the Risk Assessment of Morbidity in Paediatric Surgery (RAMPS) score[6].

However, relying on such scoring systems for risk assessment exposes inherent limitations. While tools like the PRaM score demonstrate a steady, objective risk escalation, and RAMPS provides valuable population-level insights for composite adverse events (where any adverse event, such as unplanned intensive care admissions or cardiac arrest would be put into one 'basket'), their clinical utility is often constrained by issues of generalisability. Scoring systems that are rigorously developed and validated within specific research settings or distinct native cohorts frequently experience a degradation in predictive accuracy when deployed in different clinical environments, different hospitals, or even different countries[7]. Variations in patient demographics, surgical case mixes, and local institutional workflows mean that a tool optimised for one population may lack the tailored, individualised precision required at another institution's paediatric bedside. Relying on standardised scores that may

underperform outside their derivation cohorts is counter-intuitive in the era of machine learning and artificial intelligence.

THE INITIATIVE FOR ML AND AI: ADVANTAGES AND PITFALLS

The transition from traditional scoring models to machine learning (ML) is fundamentally driven by the need to move from subjective, broad risk stratification to objective, individualised precision. Individualising risk prediction would require the collection of many variables from each patient, which requires the utilisation of ML to overcome the computational bottlenecks. Indeed, systematic reviews have consistently reported that ML models frequently outperform technical or clinical humans they have been compared with, showing improved predictive accuracy and discrimination[8].

However, in practice, computer algorithms are fundamentally context-blind, and when used incorrectly, the application of ML in risk prediction is highly susceptible to systemic errors and bias, which can occur consistently and across the board. A recent systematic review utilising the PROBAST tool revealed that approximately 90 % of published perioperative ML models exhibit a high or unclear risk of bias, largely due to a lack of external validation and inadequate handling of imbalanced datasets[9]. In medical machine learning, a class imbalance occurs when one outcome has substantially more examples than the others (see Fig. 1)[10]. In paediatric perioperative care, catastrophic outcomes such as 30-day mortality are exceedingly rare, creating severely skewed data (with the majority of patients not suffering an 'event'). If this mathematical imbalance is not explicitly corrected during the training phase, the algorithm may develop a strong preference for the majority class[11]. In practice, this means a poorly trained model could simply predict "survival" for every single patient to artificially achieve a 99.9 % accuracy rate, completely ignoring the minority class and failing to identify the patients who might actually be at high risk. More importantly, when utilising ML for risk prediction, developers must ground their algorithms in a strict clinical context. It is not enough to simply build a model; we must ask: what is the specific outcome we are trying to predict, when during the perioperative pathway are we trying to predict it, and how exactly will the clinician use the result to alter patient care[12].

The true potential of answering these questions through ML and AI is linked to the widespread adoption of Electronic Health Records (EHRs)[13]. With longitudinal health data now collected on millions of patients[14], these systems capture a highly detailed, real-world clinical footprint which includes information on diagnoses, procedures, and ongoing treatments captured at the point of care. By harnessing this multivariable clinical data, ML models can generate precise, patient-specific probabilities for adverse outcomes, which can facilitate automated, real-time clinical decision support. These ML supported systems will be able to outperform the predictive capabilities of traditional manual scores.

However, navigating this wealth of EHR data requires immense caution. In developing ML models for risk assessment, we have learned that a more careful approach - where "less is more" - is critical for clinical validity. A major pitfall in paediatric longitudinal data is the recurrent surgery bias, where the same patient may attend surgery more than once over a period of time. This can lead to statistical illusions like the "Preterm Paradox". Children with severe chronic comorbidities often return to the operating room for numerous minor, highly survivable procedures. If an algorithm is trained on data from all surgical episodes as though the episodes were separate and not linked, rather than being trained on unique patients, the algorithm may mathematically deduce that a known physiological vulnerability (like extreme prematurity) is actually a protective factor simply because it has processed many minor 'survivals' against only one tragic death. Overcoming this paradox requires a strict "Unique Patient Only" machine learning architecture to force the AI to learn actual human physiology rather than merely memorising a patient's hospital schedule. Another compelling example of the "less is more" principle is the exclusion of variables exhibiting severe multicollinearity. When highly correlated variables are simultaneously included in a model, and the algorithm is unable to recognise this multicollinearity, it confounds the algorithm's ability to isolate individual variable predictive weights, ultimately resulting in unstable, misleading, and confusing outcomes.

POINT-OF-CARE DATA AND EHR INTEGRATION

A universal truth in machine learning is that an algorithm is only as good as the data it was trained on.

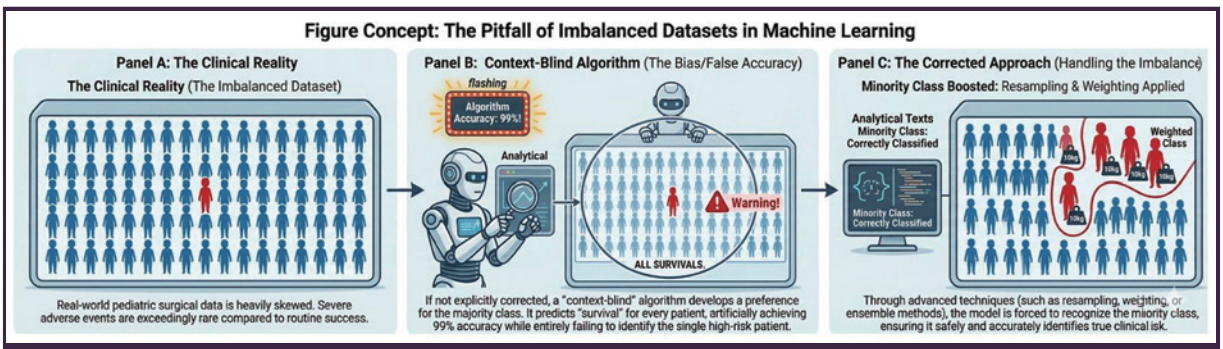

Fig. 1: The pitfall of imbalanced datasets in machine learning (Excerpted from Ishwaran H., O'Brien R. Commentary: the problem of class imbalance in biomedical data. J Thorac Cardiovasc Surg 2021;161: 1940-1941.)

The traditional reliance on free-text clinical notes creates an unstructured data environment that is virtually impossible for an algorithm to interpret reliably in real-time. To build a functional AI risk assessment tool, the foundation must be an electronic preoperative assessment form integrated directly into the Clinical Information System (CIS) at the point of care.

By utilising a mandatory, structured electronic form, the CIS actively guides the clinician through the assessment, prompting the systematic evaluation of critical subspecialty variables (such as exact weight, congenital heart disease, or renal impairment). Because the electronic form forces structured data entry, it eliminates the ambiguity of free-text. The electronic assessment form acts as a real-time data pipeline, instantly feeding objective variables into the hospital's database without the need for post-hoc manual chart extraction or abstractor bias.

Building Trust: Ensemble ML and Explainable AI

In medical AI, trusting a single "black box" algorithm is dangerous because every model has hidden blind spots and biases. To improve accuracy and reliability, it is much safer to use a "panel of experts" approach - combining multiple models. Some key ML algorithms include:

- Multivariate Logistic Regression; these algorithms serve as a transparent, linear baseline, mathematically confirming that objective data alone is highly predictive.
- Random Forest; is "non-linear", and is best at identifying extreme physiological states where risk compounds exponentially.
- eXtreme Gradient Boosting (XGBoost); which acts as a safety net, tuned explicitly to heavily penalise "false negatives" and optimised for maximum sensitivity.

The foundational concept behind this multi-layered architecture is ensemble learning, which involves generating and combining multiple algorithms, or "inducers", to solve a specific machine learning task[15]. Drawing upon the "wisdom of the crowd", this methodology relies on the premise that weighing and aggregating several individual predictions is inherently more accurate than relying on a single model[16]. By fusing different algorithms, the errors made by one inducer are likely to be compensated by the others.

The ensemble method can improve overall prediction performance , by combining several models instead of relying on just one. The combination helps prevent the model from 'overfitting' (this is when the model works well on the data it was trained on, but performs poorly on new patients). It also reduces the chance that the algorithm gets stuck during the training process and doesn't improve when new data is inputted. Ensemble methods allow the algorithms to explore a wider range of possible patterns in the data, whereas any single model would not be as flexible.

For ensemble models to work well, the individual algorithms in the ensemble need to be:

1. Different enough from each other so they don't all make the same mistakes, and
2. Each is reasonably accurate on its own.

Their individual predictions are then combined - perhaps by averaging their results or taking a majority vote. You can also instruct another model to learn how to best combine the results. The final result is a more stable and accurate prediction, which is better suited for complex clinical decision-making.

Nevertheless, high accuracy itself is not enough to earn the trust of a clinician, as the clinician need to know why an algorithm is sounding an alarm. To solve the "black box" problem of AI, we must integrate SHapley Additive exPlanations (SHAP). SHAP reverse-engineers the AI's decisions and translates complex math into something the clinician can understand, allowing doctors to see exactly which variables increased or decreased the risk.

THE DUAL UTILITY OF AI IN CLINICAL PRACTICE

The true utility of these advanced predictive models lies not in theoretical accuracy alone; they must be integrated into daily clinical practice. At the micro-level, AI provides real-time, actionable feedback directly to frontline clinicians. For instance, if the risk assessment tool is built to predict mortality and perioperative critical events, the system would provide a warning to the user for a high risk patient at the time of assessment so that appropriate clinical management would be implemented. By continuously synthesising preoperative data at the point of care, the system acts as a vigilant second set of eyes, alerting the clinician to specific physiological vulnerabilities and enabling preemptive clinical management before a crisis unfolds. At the macro-level, these individualised risk probabilities can be aggregated into a centralised operational dashboard. For a busy surgical centre managing dozens of concurrent cases, this macro-view of daily patient acuity can transform practice. It allows clinical directors to triage resources and optimise manpower allocation on the day of surgery - such as proactively deploying senior paediatric anaesthesiologists, specialised critical care nurses, or advanced airway equipment to the highest-risk operating rooms - thereby maximising both hospital efficiency and patient safety.

A compelling real-world example of this operational power recently emerged from Cincinnati Children's Hospital, which successfully deployed an automated, EHR-integrated clinical coverage scoring system for paediatric surgical patients[17]. Instead of relying on time-consuming manual chart reviews by charge nurses and clinical directors, the system continuously analysed patient variables, acute conditions, and procedural complexities to instantly stratify cases into colour-coded acuity tiers on a digital status board. At the micro-level, frontline clinicians praised the system for streamlining their workflow, noting that it functioned

as a dynamic safety checklist that updated in real-time - for example, automatically lowering a risk score if an abnormal lab result was corrected. At the macro-level, this centralised visibility allowed the anaesthesia clinical director to proactively adjust supervising ratios, ensuring 1:1 staffing for the highest-acuity cases and minimising delays caused by last-minute personnel swaps. Ultimately, through continuous, data-driven refinement, this automated system achieved over 99 % accuracy, significantly outperforming manual human identification and proving that seamlessly integrated predictive tools can successfully transform both bedside care and hospital-wide efficiency.

THE LOCAL, DYNAMIC VISION AT THE BEDSIDE - THE CONCLUSION

Ultimately, the successful integration of machine learning into perioperative care depends on recognising that predictive algorithms are not one-size-fits-all solutions. Many hospitals purchase generic, off-the-shelf AI models trained on national databases, such as the proprietary Epic Sepsis model[18] and the ACS-NSQIP risk calculators[19], but it must be remembered that patient demographics and institutional protocols vary widely. As the use of structured electronic assessment forms can capture the exact physiological profiles of specific patient cohorts over time, enabling institutions to train models entirely on their local population. Furthermore, this localised approach must be dynamic; it must function as a living risk assessment tool that is continuously validated and updated with recent data to ensure it constantly adapts to the reality of the specific hospital environment.

To ensure this technology succeeds, it must act as an invisible assistant, rather than to be seen as an extra burden by clinicians required to input the variables. The moment a clinician clicks "Save" on their preoperative assessment, the CIS can securely transmit the data to deployed ML models, calculating risk in milliseconds and returning a targeted safety alert directly to the screen. Through a tiered warning system, the AI does not replace human judgment. Instead, it provides the clinician with a mathematically rigorous, instantly accessible, and fully explainable safety net.

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Healing Notes: A Musical Journey Beyond the Emergency Room

Dr Ludwig Chun-hing TSOI

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Specialist in Emergency Medicine
Lead Vocalist, St John Band

Dr Ludwig Chun-hing TSOI

MUSIC: MY PERSONAL PRESCRIPTION

Working on the frontlines of the Emergency Department, I bear witness to the fragility of life every single day. The demanding nature of medicine - marked by long, intense working hours, unpredictable crises, and the emotional weight of patient care - often leaves us physically and mentally exhausted. While we dedicate our lives to healing others, we must also find ways to heal ourselves. For me, that ultimate remedy has been music.

My deep connection with music was born out of a profound personal adversity. In early 2017, I suddenly developed right-sided facial nerve paralysis (Bell's palsy). I could not close my right eye, my speech was slurred, and I experienced involuntary drooling. As an active, communicative physician, this loss of facial control was devastating, plunging me into a period of deep reflection and depression.

However, during this arduous rehabilitation period, a colleague suggested I use singing to train my facial muscles. I took this to heart, sought out a vocal coach, and dedicated myself to consistent practice. Not only did singing aid my physical recovery but it also soothed my soul. Later that year, I won a singing competition, which paved the way for my journey as the lead vocalist of a one-of-a-kind musical group: the St John Band.

THE BIRTH OF ST JOHN BAND

The roots of the St John Band stretch back far earlier than our current lineup, tracing to Surgeons' Night (now known as Medic's Night) between 2011 and 2012 - an annual event initiated by the Principal Medical Officer's Office (PMOO) of the Hong Kong St John Ambulance Brigade. This landmark occasion marked the beginning of doctor members actively "serving" the Brigade, with an annual dinner featuring musical performances as its earliest embryonic format. What started as casual, ad-hoc performances for the Brigade gradually evolved and consolidated over years of iterations, eventually solidifying into its current lineup.

Today, the St John Band is an all-male pop music band composed entirely of medical specialists from different disciplines. Alongside myself on vocals, the band features our band leader and guitarist Dr Eric Choy (Anaesthesiology), keyboardist Dr Jerome Wu (Neurology), bass guitarist Dr William Foo (Clinical Oncology), guitarists Dr SK Mak (Urology) and Dr Matthew Lau (ENT), with Dr Francis Lau (Orthopaedics) on the drums.

Balancing a band with seven busy specialists is no easy feat. Finding a time when none of us are on-call, doing ward rounds, or in the operating theatre requires immense coordination and sacrifice. Yet, we make it work because we share a common ethos: to use melodies to alleviate stress, balance our lives, and spread positive energy. Rehearsing and jamming together has become an essential outlet for us to escape the clinical hustle and reconnect with our creative sides.

HARMONISING HEALTHCARE WITH POP MUSIC

As an Emergency Medicine doctor, I see patients when their conditions have already deteriorated. This has instilled in me a fierce belief in "prevention over cure". The St John Band gave us a platform to transform this belief into action. We realised that medical jargon and clinic lectures can be dry and intimidating for the general public, but pop culture and music are universal. We decided to become cultural ambassadors for public health.

We began adapting classic Hong Kong pop songs into catchy public health anthems. We took the iconic Beyond track "No More Hesitation" (不再猶豫) and rewrote the lyrics to create "No More Oil and Salt" (不再油鹽), advocating for a healthier diet. Similarly, we transformed a popular "Walking in Winter" (同步過冬) into "Excessive Sugar" (糖分過高). We also adapted the oldies "Beautiful Sunday" (by Daniel Boone) to "Beautiful Kidney Day" (美麗的腎臟日), playfully warning the public about the hidden dangers of our beloved bubble teas and curry fish balls. During the darkest days of the pandemic, we adapted Beyond's "Footprints of the Past" (舊日的足跡) into "Footprints of the Pandemic" (抗疫的足跡) to boost the morale of our fellow healthcare workers and the public.

Beyond adaptations, we have also ventured into original music. Collaborating with the Department of Health, we composed "Ten Thousand Steps a Day" (挑戰萬步行), a lively, upbeat theme song that dispels the myth that exercise requires intense gym sessions. Our lyrics encourage citizens from "kindergarten to eighty"

to simply walk - whether in parks, on stairs, or along the promenade. And commissioned by the Consumer Council, we composed "Smart Choosing" (消費智惜揀), the theme song for the Smart Academy targeting secondary school students in 2025.

Fig. 1: We often meet and rehearse at midnight due to the demanding nature of our clinical commitments. Left to right: Dr Jerome Wu, Dr SK MAK, Dr Francis LAU, Dr William Foo, Dr Ludwig TSOI, Dr Eric CHOY, Dr Matthew LAU (Personal collection)

HEALING THROUGH CHARITY

Our musical footprints have extended far beyond typical concert venues, reaching various corners of the community to support charitable causes. We have performed for the World Kidney Day carnival, raised funds for cancer patients in the "Liver Bright Journey", and serenaded the elderly in community health drives.

One of my most profound experiences was collaborating with the Caritas Wong Yiu Nam Centre, a drug rehabilitation facility. Through musical rehearsals and performances, we established a non-verbal bridge of trust and acceptance with the recovering youths. I shared my own story of hitting rock bottom with facial paralysis to show them that no matter how dark life gets, resilience - and perhaps a good melody - can help you rebuild your hope. It reminded me that the essence of being a doctor is not just prescribing medication, but offering empathy, humanity, and a safe harbour in the storm.

Fig. 2: From left to right: Dr Francis LAU, Dr William FOO, SK, Dr Ludwig TSOI, Dr Eric CHOY, Dr Matthew LAU, and Dr Jerome WU (Personal collection)

LAST WORD

If there is one message I wish to pass on to my younger medical colleagues, it is this: do not let the hospital walls define your entire existence. The pursuit of medical excellence is noble, but your physical and emotional well-being is the foundation that makes that pursuit possible.

Engage in activities that ignite your passion. Whether it is music, sports, art, or writing, these pursuits do not distract from your medical career; rather, they enhance it. They teach us perseverance, teamwork, and empathy. Success in life is multifaceted. Cultivating your hobbies and spreading positive energy to the people around you will not only make you a more resilient individual, but ultimately, a better, more compassionate healer. Let us continue to inspire one another - with our stethoscopes and our songs alike.

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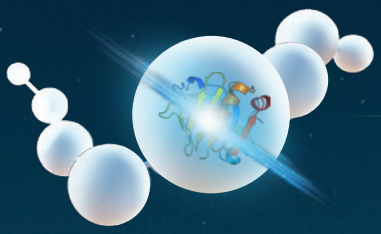

關鍵致敏蛋白*近乎0發現[1]

降低牛奶蛋白致敏性[2-4]

全新升級5HMO[5]

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*β-乳球蛋白

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Association of Private Physiotherapists of Hong Kong (APPHK): A New Chapter for the Profession

Founded in 2025 by a committed group of private physiotherapists, the Association of Private Physiotherapists of Hong Kong (APPHK) mainly acts as a representative organisation for private physiotherapists, collectively addressing the changing challenges and opportunities in the local private physiotherapy community. Its members include full members (private physiotherapists), associate members (public sector physiotherapists), and student members. Since its inception, APPHK has organised various professional seminars and social events specifically for physiotherapists to encourage ongoing education and networking.

APPHK operates with a three-fold vision to strengthen the profession internally and improve its external reputation. First, to protect industry interests, APPHK unites private physiotherapists to tackle practice-related challenges and establish mechanisms to combat unethical practices, thereby safeguarding the professional image of physiotherapy in Hong Kong. Second, to promote collaboration and business growth, APPHK offers structured channels for networking, resource sharing, and development through events and platforms, allowing members to share clinical insights and access practice management tools. Third, to improve external representation, APPHK serves as the unified voice for private physiotherapists by engaging with the government, the Legislative Council, and the insurance sector on health policies, fair reimbursement, scope of practice, and public education. Through these efforts, APPHK aims to elevate the role of physiotherapy within Hong Kong's healthcare system.

Through these initiatives, APPHK is poised to become a vital partner for private physiotherapists, helping ensure that the profession remains resilient, ethical, and progressive in a changing healthcare environment.

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黃偉健博士 Dr Clive Wai-kin WONG

Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
	★ HKMA CME Portal (Online) HKMA-KWC CME Online Lecture Series on Common Medical Conditions for GP in 2026 Topic: Metabolic Dysfunction-Associated Steatotic Liver Disease (MASLD) **1**	★ In-person / HKMA CME Portal (Online) HKMA-HKSH CME Programme 2026 Topic: Comprehensive Genomic Profiling of Cancer ★ Certificate Course on Cardiovascular Medicine 2026 (Video Lectures) **2**	**3**	★ Certificate Course on Clinical Nutrition and Disease Management 2026 (Video Lectures) **4**	★ In-person The HKMA CME Lecture in Physical Attendance Mode Topic: Vasomotor Symptoms - Advanced Therapy to Address The Common Concern from Menopausal Women ★ HKMA CME Portal (Online) The HKMA CME Online Evening Lecture Topic: Optimising Real-World cGVHD Care: Maximizing Outcomes, Minimizing Infection Risk **5**	**6**
7	**8**	★ Certificate Course on Cardiovascular Medicine 2026 (Video Lectures) **9**	★ The Hong Kong Neurosurgical Society Monthly Academic Meeting - To be confirmed ★ HKMA CME Portal (Online) The HKMA CME Online Lecture Topic: Acne, Acne Scars and Related Complications **10**	★ HKMA CME Portal (Online) The HKMA CME Online Lecture Topic: Redefining Standard Practice in Post-PCI Antiplatelet Therapy ★ Certificate Course on Clinical Nutrition and Disease Management 2026 (Video Lectures) **11**	**12**	**13**
14	**15**	★ HKMA CME Portal (Online) The HKMA CME Online Lecture Topic: Bridging the Gap in Atopic Dermatitis Management: Addressing Corticophobia by Other Treatment Options **16**	**17**	★ In-person / HKMA CME Portal (Online) The HKMA CME Hybrid Lecture Topic: Long-Term Outcomes with IL-23i in Moderate-to-Severe Psoriasis ★ Certificate Course on Clinical Nutrition and Disease Management 2026 (Video Lectures) **18**	**19**	**20**
21	**22**	★ In-person The HKMA CME Lecture in Physical Attendance Mode Topic: Primary Care Approach to Hemorrhoidal Disease ★ Certificate Course on Practical Ultrasound Approach to Common Clinical Problems 2026 - from Basic to Advance (Video Lectures) **23**	★ HKMA CME Portal (Online) The HKMA Adult Immunisation Campaign 2026 CME Online Lecture Topic: Meningococcal Infection 2026: From UK to Hong Kong - Risk Stratification and Prevention ★ In-person / HKMA CME Portal (Online) The HKMA CME Hybrid Evening Lecture Topic: From Evidence to Engagement: Addressing COVID 19 Disease Burden and Vaccine Hesitancy **24**	★ Certificate Course on Clinical Nutrition and Disease Management 2026 (Video Lectures) ★ FMSHK Executive Committee Meeting **25**	★ In-person The HKMA CME Lecture in Physical Attendance Mode Topic: Transforming Diabetes Care: The Role of Dpp-4 Inhibitors for Patients with Special Needs **26**	**27**
28	**29**	★ Certificate Course on Practical Ultrasound Approach to Common Clinical Problems 2026 - from Basic to Advance (Video Lectures) **30**				

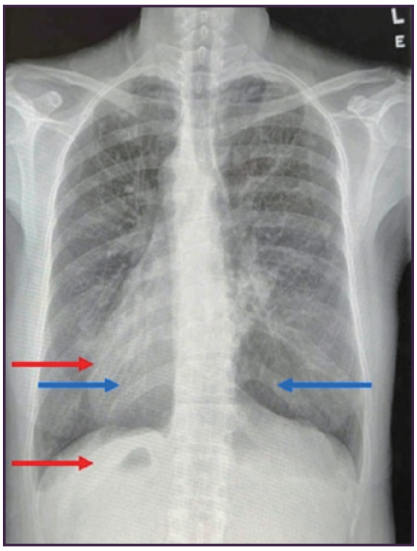
Date / Time	Function	Enquiry / Remarks
1 MON 2:00 PM	**HKMA CME Portal (Online)** **HKMA-KWC CME Online Lecture Series on Common Medical Conditions for GP in 2026** Topic: Metabolic Dysfunction-Associated Steatotic Liver Disease (MASLD) Organisers: The Hong Kong Medical Association and Kowloon West Cluster of HA Speaker: Dr Reggie Siu-ting LI	HKMA CME Dept. 2527 8452 1 CME Point
2 TUE 2:00 PM	**In-person / HKMA CME Portal (Online)** **HKMA-HKSH CME Programme 2026** **Topic: Comprehensive Genomic Profiling of Cancer** Organisers: The Hong Kong Medical Association and Hong Kong Sanatorium & Hospital Speaker: Dr Edmond Shiu-kwan MA Venue: The HKMA Wanchai Premises, 5/F, Duke of Windsor Social Service Building, 15 Hennessy Road, Wanchai, Hong Kong	HKMA CME Dept. 2527 8452 1 CME Point
7:00 PM	**Certificate Course on Cardiovascular Medicine 2026 (Video Lectures)** Organisers: The Federation of Medical Societies of Hong Kong & Hong Kong College of Cardiology Speakers: Dr Tsun-kwong LAI & Dr Kwok-ho YAU	Ms ToTo CHAN Tel: 2821 3512
4 THU 7:00 PM	**Certificate Course on Clinical Nutrition and Disease Management 2026 (Video Lectures)** Organisers: The Federation of Medical Societies of Hong Kong & Hong Kong Dietitians Association Speaker: Ms Denise LUK	Ms ToTo CHAN Tel: 2821 3512
5 FRI 2:00 PM	**In-person** **The HKMA CME Lecture in Physical Attendance Mode** **Topic: Vasomotor Symptoms – Advanced Therapy to Address The Common Concern from Menopausal Women** Organiser: The Hong Kong Medical Association Speaker: Dr Cheryl Yuen-ching CHAN Venue: The HKMA Central Clubhouse, 2/F, Chinese Club Building, 21-22 Connaught Road Central, Central	HKMA CME Dept. 2527 8452 1 CME Point
7:30 PM	**HKMA CME Portal (Online)** **The HKMA CME Online Evening Lecture** **Topic: Optimising Real-World cGVHD Care: Maximizing Outcomes, Minimizing Infection Risk** Organiser: The Hong Kong Medical Association Speakers: Prof Yok-lam KWONG, Dr Yoshihiro INAMOTO, Prof David MICHONNEAU and Dr Garret Man-kit LEUNG	HKMA CME Dept. 2527 8452 1.5 CME Points
9 TUE 7:00 PM	**Certificate Course on Cardiovascular Medicine 2026 (Video Lectures)** Organisers: The Federation of Medical Societies of Hong Kong & Hong Kong College of Cardiology Speakers: Dr Thomas CHIM & Dr Yuen-fung YIU	Ms ToTo CHAN Tel: 2821 3512
10 WED 7:30 AM	**The Hong Kong Neurosurgical Society Monthly Academic Meeting - To be confirmed** **Organiser: Hong Kong Neurosurgical Society** Speaker(s): Dr Gabriel Tze-chung WU Chairman: Dr Alberto Chi-ho CHU Venue: Seminar Room, G/F, Block A, Queen Elizabeth Hospital; or via Zoom meeting	CME Accreditation College: 1.5 points College of Surgeons of Hong Kong Enquiry : Dr Jason CHOW Tel: 2595 6456 Fax. No.: 2965 4061
2:00 PM	**HKMA CME Portal (Online)** **The HKMA CME Online Lecture** **Topic: Acne, Acne Scars and Related Complications** Organiser: The Hong Kong Medical Association Speaker: Dr Hok-fai CHENG	HKMA CME Dept. 2527 8452 1 CME Point
11 THU 2:00 PM	**HKMA CME Portal (Online)** **The HKMA CME Online Lecture** **Topic: Redefining Standard Practice in Post-PCI Antiplatelet Therapy** Organiser: The Hong Kong Medical Association Speaker: Dr Mo-chee CHAU	HKMA CME Dept. 2527 8452 1 CME Point
7:00 PM	**Certificate Course on Clinical Nutrition and Disease Management 2026 (Video Lectures)** Organisers: The Federation of Medical Societies of Hong Kong & Hong Kong Dietitians Association Speaker: Ms Sylvia LAM	Ms ToTo CHAN Tel: 2821 3512
16 TUE 2:00 PM	**HKMA CME Portal (Online)** **The HKMA CME Online Lecture** **Topic: Bridging the Gap in Atopic Dermatitis Management: Addressing Corticophobia by Other Treatment Options** Organiser: The Hong Kong Medical Association Speaker: Dr Dominic Yik-kiu LAI	HKMA CME Dept. 2527 8452 1 CME Point
18 THU 2:00 PM	**In-person / HKMA CME Portal (Online)** **The HKMA CME Hybrid Lecture** **Topic: Long-Term Outcomes with IL-23i in Moderate-to-Severe Psoriasis** Organiser: The Hong Kong Medical Association Speaker: Dr Davis Yung CHAN Venue: The HKMA Central Clubhouse, 2/F, Chinese Club Building, 21-22 Connaught Road Central, Central	HKMA CME Dept. 2527 8452 1 CME Point
7:00 PM	**Certificate Course on Clinical Nutrition and Disease Management 2026 (Video Lectures)** Organisers: The Federation of Medical Societies of Hong Kong & Hong Kong Dietitians Association Speaker: Ms Heidi CHAN	Ms ToTo CHAN Tel: 2821 3512
23 TUE 2:00 PM	**In-person** **The HKMA CME Lecture in Physical Attendance Mode** **Topic: Primary Care Approach to Hemorrhoidal Disease** Organiser: The Hong Kong Medical Association Speaker: Dr Winnie Hoi-man LI Venue: Maggie Room, 2/F, Eaton HK Hotel, 380 Nathan Road, Kowloon	HKMA CME Dept. 2527 8452 1 CME Point

Date / Time	Function	Enquiry / Remarks
23 TUE 7:00 PM	**Certificate Course on Practical Ultrasound Approach to Common Clinical Problems 2026 - from Basic to Advance (Video Lectures)** Organisers: The Federation of Medical Societies of Hong Kong & Hong Kong Society for Ultrasound in Medicine Speaker: Dr Hoi-to LAU	Ms ToTo CHAN Tel: 2821 3512
24 WED 2:00 PM	**HKMA CME Portal (Online)** **The HKMA Adult Immunisation Campaign 2026 CME Online Lecture** **Topic: Meningococcal Infection 2026: From UK to Hong Kong - Risk Stratification and Prevention** Organiser: The Hong Kong Medical Association Speaker: Dr Alfred Yat-cheung TAM	HKMA CME Dept. 2527 8452 1 CME Point
8:00 PM	**In-person / HKMA CME Portal (Online)** **The HKMA CME Hybrid Evening Lecture** **Topic: From Evidence to Engagement: Addressing COVID 19 Disease Burden and Vaccine Hesitancy** Organiser: The Hong Kong Medical Association Speaker: Dr Hoe-nam LEONG Venue: Salon II-III & IV-V, Lobby Level, Hyatt Regency Hong Kong, Tsim Sha Tsui, Hong Kong	HKMA CME Dept. 2527 8452 1 CME Point
25 THU 7:00 PM	**Certificate Course on Clinical Nutrition and Disease Management 2026 (Video Lectures)** Organisers: The Federation of Medical Societies of Hong Kong & Hong Kong Dietitians Association Speaker: Ms Ingrid KAN	Ms ToTo CHAN Tel: 2821 3512
7:30 PM	**FMSHK Executive Committee Meeting** Organiser: The Federation of Medical Societies of Hong Kong Venue: Council Chamber, 4/F, Duke of Windsor Social Service Building, 15 Hennessy Road, Wanchai, Hong Kong	Ms Mabel TSANG Tel: 2527 8898
26 FRI 2:00 PM	**In-person** **The HKMA CME Lecture in Physical Attendance Mode** **Topic: Transforming Diabetes Care: The Role of Dpp-4 Inhibitors for Patients with Special Needs** Organiser: The Hong Kong Medical Association Speaker: Dr Tai-pang IP Venue: The HKMA Central Clubhouse, 2/F, Chinese Club Building, 21-22 Connaught Road Central, Hong Kong	HKMA CME Dept. 2527 8452 1 CME Point
30 TUE 7:00 PM	**Certificate Course on Practical Ultrasound Approach to Common Clinical Problems 2026 - from Basic to Advance (Video Lectures)** Organisers: The Federation of Medical Societies of Hong Kong & Hong Kong Society for Ultrasound in Medicine Speaker: Dr Andrew LI	Ms ToTo CHAN Tel: 2821 3512

Answers to Radiology Quiz

Answers:

1. Situs inversus, as evidenced by the right cardiac apex and gastric bubble in the right upper abdomen (Red arrows). Tram-track opacities over bilateral lower zones, suggestive of bronchiectasis (Blue arrows).



2. Kartagener's syndrome.

3. CT Thorax to confirm bronchiectasis. CT Sinuses to look for sinusitis changes. Genetic workup to confirm diagnosis of Kartagener's syndrome.

Dr Andrew Man-kwun LI
ScB, MBBS, FRCR

First-line Treatment for ADHD Recommended by International Guidelines and Consensus[1-4]

Ritalin LA®
Methylphenidate Hydrochloride

American Academy of Pediatrics
DEDICATED TO THE HEALTH OF ALL CHILDREN™

CADDRA
CANADIAN ADHD RESOURCE ALLIANCE

NICE
National Institute for Health and Care Excellence

European Network ADULT ADHD

Onset of Action at 1 to 1.5 hours[5]

1-1.5 hrs

Bimodal release for reduced pharmacokinetic fluctuation[6]

Flexibility on administration[7]

- Swallow as whole capsule or sprinkle the contents on soft food

2-year prospective, longitudinal, controlled study on ADHD eased safety concern over long-term MPH use[8]

No growth reduction at 2 years[8]

No statistical differences between MPH treatment group and non-treatment group on

Height velocity
Difference in log score

-0.07

(95%CI -0.18 to 0.04; p=0.20)

Log height velocity SD score
MPH treatment –0.04
MPH non-treatment 0.03

Weight velocity
Difference in log score

-0.02

(95%CI -0.09 to 0.05; p=0.64)

Log weight velocity SD score
MPH treatment 0.02
MPH non-treatment 0.04

BMI
Difference in log score

0.00

(95%CI -0.03 to 0.04; p=0.99)

Log BMI
MPH treatment 2.91
MPH non-treatment 2.91

The most common adverse events (≥5%) in children are headache, insomnia, upper abdominal pain, anorexia, decreased appetite, nasopharyngitis, irritability and lethargy[7]

Study design: The study of naturalistic, longitudinal and controlled nature was a part of the ADDUCE research programme in 27 European child and adolescent mental health centres in the United Kingom, Germany, Switzerland, Italy and Hungary. Children and adolescents aged 6-17 years were recruited into three cohorts: medication-naive ADHD patients who intended to start MPH treatment, medication-naive ADHD patients who did not intend to start any ADHD medication, and a control group without ADHD. It aimed to evaluate the long-term effects of MPH on growth and development, neurological health, psychiatric health, sexual development and fertility, and cardiovascular responses in ADHD children and adolescents. The primary outcome was height velocity.

ADHD= attention deficit hyperactivity disorder; CI= confidence interval; MPH= methylphenidate; SD= standard deviation.

References: 1. Wolraich ML, et al. Pediatrics 2019;144(4):e20191682. 2. Canadian ADHD Resource Alliance (CADDRA). Canadian ADHD Practice Guidelines, Fourth Edition. CADDRA 2018. 3. National Institute for Health and Care Excellence. Attention deficit hyperactivity disorder: diagnosis and management 2018. Available at: www.nice.org.uk/guidance/ng87 (Accessed on: 30 Dec 2024). 4. Kooij JJS, et al. Eur Psychiatry 2019;56:14-34. 5. Brams M, et al. Postgrad Med 2008;120:69-88. 6. Wang Y, et al. Biopharm Drug Dispos. 2004 Mar;25(2):91-8. 7. Ritalin® 10/ Ritalin® LA Hong Kong Prescribing Information. 8. Man KKC, et al. Lancet Psychiatry. 2023 May;10(5):323-333.

Ritalin® / Ritalin® LA

Important note: Before prescribing, consult full prescribing information. **Presentation:** ♦ Immediate-release (Ritalin®) tablets containing 10 mg methylphenidate hydrochloride. ♦ Modified-release capsules (Ritalin® LA) containing 10 mg, 20 mg or 30 mg methylphenidate hydrochloride. **Indications:** Attention-deficit/hyperactivity disorder (ADHD) in children aged 6 years and older; ADHD in adults (Ritalin® LA only); narcolepsy (Ritalin® tablets only) in adults. **Dosage and administration:** **ADHD:** *Children (6 years and over)* Ritalin® Tablets: ♦ For children, start with 5 mg once or twice daily and increase in increments of 5 to 10 mg weekly. Ritalin® LA Capsules: ♦ for patients who are currently **not** taking methylphenidate: starting dose is 20 mg. Patients may begin treatment with Ritalin® LA 10 mg if necessary. ♦ for patients who are currently taking methylphenidate: the recommended dose of Ritalin® LA should be equal to the total daily dose of the immediate-release formulation ♦ Daily dosage should not exceed 60 mg. ♦ Ritalin® LA dosage may be adjusted at weekly intervals in 10 mg increments for children ♦ Ritalin® LA is for once daily administration. *Adult:* ♦ Only the Ritalin® LA formulation should be used for the treatment of ADHD in adults. ♦ for patients who are currently not taking methylphenidate: starting dose is 20 mg. ♦ for patients who are currently taking methylphenidate: the recommended dose of Ritalin® LA should be equal to the total daily dose of the immediate-release formulation ♦ Daily dosage should not exceed 80 mg. ♦ Use of Ritalin® LA in patients over 60 years of age has not been studied in controlled trials. ♦ Ritalin® LA dosage may be adjusted at weekly intervals in 20 mg increments for adults. ♦ Ritalin® LA is for once daily administration. **Narcolepsy:** ♦ Daily dosage should not exceed 60 mg. ♦ For adults treated for narcolepsy, the usual daily dose is 20 to 30 mg. **Contraindications:** ♦ anxiety and tension states, agitation, a family history or diagnosis of Tourette's syndrome, glaucoma, hyperthyroidism, pre-existing cardiovascular disorders including uncontrolled hypertension, angina pectoris, arterial occlusive disease especially coronary arteries; heart failure, haemodynamically significant congenital heart disease, cardiomyopathies, myocardial infarction, cardiac arrhythmia and channelopathies (disorders caused by the dysfunction of ion channels), treatment with monoamine oxidase inhibitors, and also within a minimum of 14 days following discontinuation of a monoamine oxidase inhibitor (hypertensive crises may result), phaeochromocytoma, known drug dependence or alcohol abuse; severe depression, anorexia nervosa, psychotic symptoms or suicidal tendency, since Ritalin® might worsen these conditions; known hypersensitivity to methylphenidate or to any component of the formulation. **Warnings and precautions:** ♦ Treatment with methylphenidate is not indicated in all cases of ADHD and should be considered only after detailed history taking and evaluation of the patient. The decision to prescribe methylphenidate should depend on the physician's assessment of the chronicity and severity of the symptoms and in paediatric patients, the appropriateness to the child's age. Prescription should not depend solely on the presence of isolated behavioural characteristics. When the symptoms are associated with acute stress reactions, treatment with methylphenidate is usually not indicated. ♦ Generally should not be used in patients with structural cardiac abnormalities or other serious cardiac disorders that may increase the risk of sudden death. ♦ Pre-existing cardiovascular disorders, a family history of sudden death and ventricular arrhythmia should be assessed before initiating treatment. ♦ Caution in patients with pre-existing hypertension. Blood pressure should be monitored during treatment. ♦ Patients who develop symptoms suggestive of cardiac disease should undergo prompt cardiac evaluation. Misuse of stimulants of the central nervous system may be associated with sudden death and other serious cardiovascular adverse events. ♦ Patients with pre-existing cerebrovascular abnormalities should not be treated with Ritalin®. ♦ Patients with additional risk factors (history of cardiovascular disease, concomitant medications that elevate blood pressure) should be assessed regularly for neurological/psychiatric signs and symptoms. ♦ Pre-existing psychiatric disorders and a family history of psychiatric disorders should be assessed before initiating treatment. ♦ Should not be initiated in patients with acute psychosis, acute mania or acute suicidality. ♦ In case of emergent psychiatric symptoms (e.g. hallucinations or mania, aggressive behaviour and suicidal tendency) or exacerbation of pre-existing psychiatric symptoms, Ritalin® should not be given to patients unless the benefit outweighs the potential risk. ♦ Patients and caregivers should be alerted about the need to monitor for suicidal thoughts and unusual changes in behavior and to seek immediate medical attention. ♦ Family history should be assessed and clinical evaluation for tics or Tourette's syndrome in children should precede ADHD treatment. ♦ Patients should be regularly monitored for the emergence or worsening of tics during initiating treatment. ♦ Growth should be monitored during treatment as clinically necessary, treatment interruption may be considered. ♦ Caution in patients with epilepsy. ♦ Patients who develop priapism should seek immediate medical attention. ♦ Not recommended together with serotonergic drugs due to risk of serotonin syndrome. ♦ Chronic abuse can lead to marked tolerance and psychological dependence. ♦ Caution in emotionally unstable patients. ♦ Careful supervision during withdrawal. ♦ Patients requiring long-term therapy should be carefully monitored. Consider appropriate medical intervention in the event of hematological disorders. ♦ Ritalin®-treated patients considered at risk for acute angle closure glaucoma (e.g., patients with significant hyperopia) should be evaluated by an ophthalmologist. ♦ Close monitoring of Ritalin®-treated patients with a history of abnormally increased IOP or glaucoma is recommended. ♦ Should not be used for children under 6 years of age. ♦ Patients should refrain from driving and using machinery if dizziness, drowsiness, blurred vision, hallucinations or other CNS side effects occur. ♦ Prolonged and painful erections, sometimes requiring surgical intervention, have been reported with methylphenidate products in both pediatric and adult patients. Priapism was not reported with drug initiation but developed after some time on the drug, often subsequent to an increase in dose. Priapism has also appeared during a period of drug withdrawal (drug holidays or discontinuation). Patients who develop abnormally sustained or frequent and painful erections should seek immediate medical attention. **Pregnancy, lactation, females and males of reproductive potential Pregnancy:** ♦ Ritalin® should not be given to pregnant women unless the potential benefit outweighs the risk to the fetus. **Lactation:** ♦ Case reports showed that methylphenidate was distributed into breast milk. A decision should be made whether to abstain from breast-feeding or to abstain from Ritalin® therapy, taking into account the benefit of breast-feeding to the child and the benefit of therapy to the woman. **Adverse drug reactions: Very common (≥10%):** nasopharyngitis, decreased appetite, nervousness, insomnia, nausea, dry mouth, irritability. **Common (≥1 to <10%):** anxiety, restlessness, sleep disorder, agitation, depression, aggression, bruxism, tremor, dyskinesia, headache, drowsiness, dizziness, tachycardia, palpitation, arrhythmias, changes in blood pressure and heart rate (usually an increase), cough, abdominal pain, vomiting (which may be alleviated by concomitant food intake), dyspepsia, toothache, rash, pruritus, urticaria, fever, scalp hair loss, hyperhidrosis, arthralgia, feeling jittery, decreased weight, Raynaud's phenomenon, peripheral coldness. **Uncommon (≥0.1 to <1%):** trismus. **Rare (≥0.01 to <0.1%):** difficulties in visual accommodation, blurred vision, angina pectoris, moderately reduced weight gain and slight growth retardation during prolonged use in children. **Very rare (<0.01%):** leucopenia, thrombocytopenia, anaemia, hypersensitivity reactions, including angioedema and anaphylaxis, hyperactivity, psychosis (sometimes with visual and tactile hallucinations), transient depressed mood, convulsions, choreoathetoid movements, tics or exacerbation of existing tics and Tourette's syndrome, cerebrovascular disorders including vasculitis, cerebral haemorrhages and cerebrovascular accidents, reports of poorly documented neuroleptic malignant syndrome, abnormal liver function, ranging from transaminase elevation to hepatic coma, thrombocytopenic purpura, exfoliative dermatitis, erythema multiforme, muscle cramps. **Unknown**: pancytopenia, dysphemia, suicidal ideation or attempt (including completed suicide), irritability, affect lability, abnormal thinking or behaviour, anger, altered mood, mood swings, hypervigilance, mania, disorientation, libido disorder, apathy, stereotypy, change in sustained attention, confusional state, drug abuse and drug dependence, reversible ischemic neurological deficit, migraine, diplopia, mydriasis, visual impairment, auricular swelling, cardiac arrest, myocardial infarction, laryngeal pain, dyspnoea, epistaxis, diarrhoea, constipation, erythema, fixed eruption, myalgia, muscle twitching, priapism, erectile dysfunction, gynaecomastia, chest pain, fatigue, enuresis, increased intraocular pressure. Very rare reports of poorly documented neuroleptic malignant syndrome (NMS) have been received. In most of these reports, patients were also receiving other medications. It is uncertain what role Ritalin® played in these cases. ***Reported with other methylphenidate-containing products:*** hypersensitivity reactions such as auricular swelling, haematuria, incontinence, sudden cardiac death, cardiac murmur. **Interactions:** ♦ **Concomitant use contraindicated:** MAO inhibitors (currently or within the preceding 2 weeks). ♦ Caution when used concomitantly with drugs that elevate blood pressure, coumarin anticoagulants, anticonvulsants, centrally acting alpha-2 agonists (e.g. clonidine), direct and indirect dopaminergic drugs (e.g. tricyclic antidepressants, DOPA, antipsychotics); phenylbutazone. Monitoring of extrapyramidal symptoms is recommended when antipsychotics are used concomitantly. ♦ **Alcohol:** Patients should abstain from alcohol during treatment. ♦ Ritalin® should not be taken on the day of a planned surgery due to risk of sudden blood pressure increase during surgery. ♦ May induce false positive laboratory tests for amphetamines. ♦ Risk of serotonin syndrome with concomitant use of methylphenidate and serotonergic drugs. **Packs and prices:** ♦ Ritalin® Tablets: 10 mg (200s) ♦ Ritalin® LA Capsules: 10 mg (30's), 20 mg (30's and 100's) and 30 mg (30's) **Legal classification:** P1S1S3 Revision Date: 01 Apr 2025 Ref: Australia Jan 2024 (including 1239s + 1371s) + Apr 2024 DoH request

This material for RITALIN® / RITALIN® LA is approved for use only in Hong Kong. Prescribing information may vary depending on local approval in each country/location.
Before prescribing any product, always refer to local materials such as the prescribing information and/or the Summary of Product Characteristics (SPC).

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