

The Future of Allergy Management: How Artificial Intelligence Is Changing the Game



Giovanna Cilluffo, PhD^{a,b}, Sakina Bajowala, MD^c, Tania Elliott, MD^d, Payel Gupta, MD, FAAAAI^e, Sofija Volertas, MD^f, and Giuliana Ferrante, MD, PhD^{g,h} *Palermo, Rome, and Verona, Italy; North Aurora, IL; New York, NY; and Chapel Hill, NC*

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Learning objectives:

1. Discuss current and potential applications of artificial intelligence (AI) and machine learning in healthcare.
2. Understand both the risks and benefits of AI integration in practice.
3. Identify specific use-cases for AI in allergy/immunology practice.
4. Explain how AI can improve physician performance and reduce workload.

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Allergy management is undergoing a transformative shift due to advancements in diagnostic tools, precision medicine, and digital health technologies. Artificial intelligence-driven predictive models enable more personalized and accurate diagnoses. In addition, digital health solutions are enhancing

patient monitoring and adherence to treatment protocols. The integration of these advances into clinical practice requires interdisciplinary collaboration and updated health care policies to ensure accessibility and affordability. Although these innovations present promising opportunities, challenges such as

^aDepartment of Earth and Marine Sciences, University of Palermo, Palermo, Italy

^bNational Interuniversity Consortium for Marine Sciences (CoNISMa), Rome, Italy

^cKaneland Allergy and Asthma Center, North Aurora, IL

^dDepartment of Medicine, NYU Langone Health, New York, NY

^eDivision of Allergy & Immunology, Department of Internal Medicine, Mount Sinai Medical Center, New York, NY

^fDivision of Rheumatology, Allergy & Immunology, Department of Internal Medicine, University of North Carolina at Chapel Hill, Chapel Hill, NC

^gDepartment of Surgery, Dentistry, Pediatrics and Gynecology, Pediatric Division, University of Verona, Verona, Italy

^hInstitute of Translational Pharmacology (IFT), National Research Council (CNR), Palermo, Italy

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Corresponding author: Giovanna Cilluffo, PhD, Department of Earth and Marine Sciences, University of Palermo, Via Archirafi 18, 90123, Palermo, Italy. E-mail: giovanna.cilluffo@unipa.it.

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Abbreviations used

AD- Atopic dermatitis
 AI- Artificial intelligence
 AIT- Allergen immunotherapy
 AMIA- American Medical Informatics Association
 AR- Allergic rhinitis
 ARF-OOBEE- Adaptive Random Forest—Out-of-Bag—Easy Ensemble
 ARIA- Allergic Rhinitis and its Impact on Asthma
 AUC- Area under the curve
 CCL- Chemokine ligands
 CNN- Convolutional neural network
 CRSwNP- Chronic rhinosinusitis with nasal polyps
 CXCL- C-X-C Motif Chemokine Ligand 1
 EASI-75- Eczema Area and Severity Index-75
 EHRs- Electronic health records
 IgE- Immunoglobulin E
 IL- Interleukin
 k-NN- K-nearest neighbors
 LSTM- Long short-term memory
 ML- Machine learning
 MLP- Multi-layer perceptron
 SCIT- Subcutaneous immunotherapy
 SCORAD- SCORing Atopic Dermatitis
 SLAC- Stochastic latent actor-critic
 SNOT-22- Sino-Nasal Outcome Test-22
 SVM- Support vector machine
 T2- T2 helper
 WAO- World Allergy Organization

data privacy, regulatory approval, and equitable health care distribution must be addressed. By embracing technological and scientific developments, the future of allergy management aims to improve patient outcomes, enhance quality of life, and reduce the overall burden of allergic diseases globally. © 2025 The Authors. Published by Elsevier Inc. on behalf of the American Academy of Allergy, Asthma & Immunology. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>). (J Allergy Clin Immunol Pract 2025;13:2877-89)

Key words: Artificial intelligence; Machine learning; Allergic diseases; Allergy management; Global burden

INTRODUCTION

Allergic diseases, including asthma, allergic rhinitis (AR), food allergies, and atopic dermatitis (AD), have emerged as a major global health problem, affecting hundreds of millions of people worldwide. The prevalence of these conditions has been steadily increasing over the past few decades. In 2019, it was estimated that approximately 81 million children suffered from asthma, and 5.6 million children were diagnosed with AD globally.¹ Furthermore, data from the World Allergy Organization (WAO) indicate that up to 40% of the global population exhibits sensitization to environmental allergens, as evidenced by the presence of allergen-specific immunoglobulin E (IgE) antibodies.² Allergic diseases impose a significant burden on health care systems, economies, and individual quality of life, leading to increased morbidity and, in severe cases, life-threatening

reactions such as anaphylaxis.³⁻⁵ Given the heterogeneity of allergic diseases and their underlying mechanisms, conventional diagnostic and therapeutic approaches may be unsuccessful to provide precise, personalized care. Indeed, evidence show that patients can undergo trial-and-error treatments leading to sub-optimal disease control, increased health care expenditures, and diminished quality of life.^{6,7} The growing recognition of the need for personalized approaches to allergy management has driven the interest of researchers and clinicians in innovative technologies capable of integrating multifactorial data to guide precise therapeutic decisions. In particular, the limitations of current allergy diagnostics and treatment paradigms necessitate novel data-driven approaches that can improve disease identification, personalize management strategies, and predict disease progression with greater accuracy. Artificial intelligence (AI) has emerged as a transformative technology in modern medicine, offering promising solutions for the analysis of complex datasets, pattern recognition, and decision support in clinical practice. The AI covers a suite of computational techniques, including machine learning (ML), deep learning, natural language processing, and big data analytics, all of which have demonstrated remarkable success in disease prediction, diagnostic imaging, and treatment optimization across various medical fields such as oncology, cardiology, and neurology.⁸ Given these advancements, AI holds significant potential to revolutionize allergy traditional management (Figure 1) by addressing key gaps in diagnostic accuracy, risk stratification, and therapy personalization⁹ but also through patient empowerment.

Recent studies have demonstrated the efficacy of AI-driven approaches in allergy and immunology research. For instance, ML models have been employed to improve the endotyping of childhood AR, leading to advanced diagnostic accuracy and tailored therapeutic interventions within the framework of precision medicine.^{10,11} Similarly, ML-based algorithms have facilitated a deeper understanding of pediatric asthma heterogeneity, allowing for the identification of distinct disease phenotypes with potential clinical implications.¹² Furthermore, AI-driven models have been utilized to predict patient responses to allergen immunotherapy, enabling the development of targeted treatment regimens and reducing unnecessary exposure to ineffective therapies. Despite its vast potential, the implementation of AI in health care presents relevant challenges, including ethical considerations, data privacy concerns, and the need for rigorous clinical validation. Moreover, algorithmic bias, model interpretability, and integration with existing health care infrastructure remain critical areas for further exploration.

The ML is a branch of AI that focuses on the development of algorithms capable of learning patterns from data and making decisions or predictions based on it. Various models have been developed to address different types of problems ranging from classification and regression to clustering and dimensionality reduction.¹² Table I summarizes the main ML models highlighting strengths and limitations of each model.

When evaluating the performance of an ML model, the choice of metric is highly dependent on the nature of the task, for example, classification or regression. Table II reports the main performance metrics used.

This review aims to explore the specific applications of AI in the management of allergic diseases. We examine the practical and ethical challenges associated with the implementation of AI in allergy care, including the need for clinical validation,

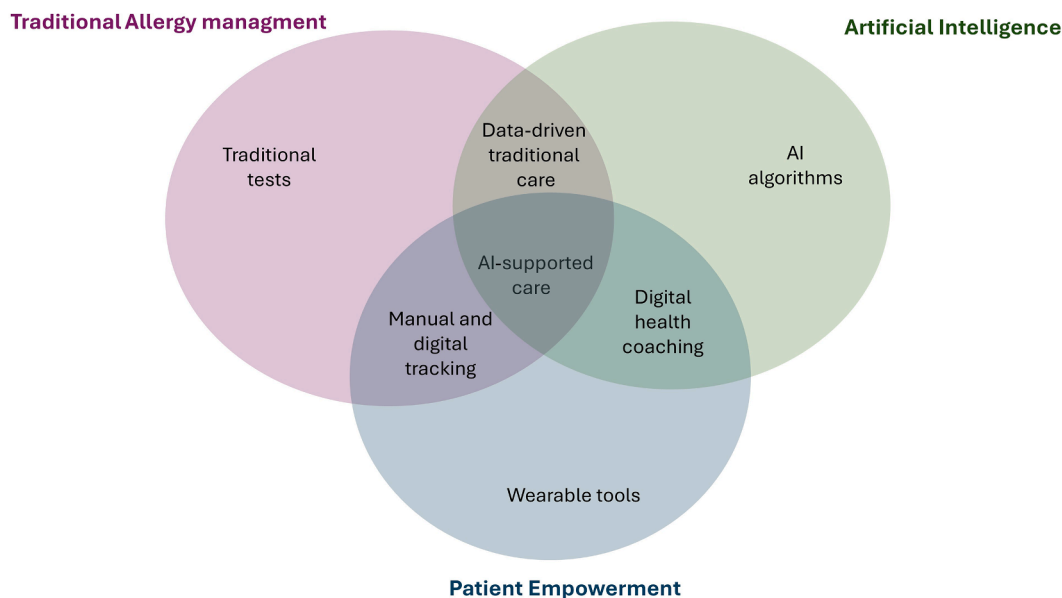


FIGURE 1. Integration of AI and allergy management.

TABLE I. Summary of the main ML models

Model	Type	Key characteristics	Strengths	Limitations
Linear regression	Regression	Assumes linear relationship between features and target	Simple, interpretable	Poor for complex/nonlinear patterns
Logistic regression	Classification	Models binary outcomes using sigmoid function	Interpretable, effective for linearly separable data	Limited in complex classification tasks
k-NN	Both	Instance-based; classifies by majority vote among “k” nearest neighbors	No training time, intuitive	Sensitive to distance metric; slow for large datasets
Decision trees	Both	Uses hierarchical rules to split data	Easy to visualize and interpret	Prone to overfitting
Random forest	Both	Ensemble of decision trees using bagging	Reduces overfitting, robust	Less interpretable than single tree
XGBoost	Both	Gradient boosting of trees, improves previous trees’ errors	High accuracy, handles missing data	Complex, requires tuning
SVM	Classification	Finds optimal hyperplane to separate classes	Effective in high dimensions	Computationally intensive for large datasets
Naive Bayes	Classification	Based on Bayes theorem with strong independence assumption	Fast, works well with high-dimensional data	Unrealistic independence assumption
ANN/MLP	Both	Layers of neurons; can model nonlinear relationships	Very powerful for complex patterns	Requires large data, black-box nature
Voting classifier	Ensemble	Combines multiple model outputs using majority vote or average	Simple and effective ensemble	Does not model intermodel dependencies
Stacking	Ensemble	Uses predictions from base models as input for a meta-model	Flexible, powerful	More complex, risk of overfitting

ANN, Artificial neural network; MLP, multi-layer perceptron.

algorithmic bias, and privacy concerns. By addressing these issues, we aim to highlight both the opportunities and the limitations of AI in allergy research and health care, opening the way for future innovations in personalized allergy management.

PRECISION DIAGNOSIS THROUGH AI

Precision medicine is an emerging approach that tailors health care by leveraging individual characteristics to optimize treatment

and improve health outcomes. Its primary goal is to customize care through the identification of clinical, biological, or genetic markers. This enables the development of diagnostic, prognostic, and therapeutic strategies tailored to each patient’s specific needs.¹³ The integration of AI has the potential to revolutionize precision medicine by enhancing accuracy, efficiency, and personalization in patient care.¹⁰ Approaches driven by AI approaches, such as ML and deep learning models, enable the analysis of complex immunological patterns, genetic predispositions, and environmental

TABLE II. Summary of evaluation metrics

Task	Metric	Description	Strengths	Limitations
Classification	Accuracy	Ratio of correct predictions	Simple to understand	Misleading with imbalanced data
Classification	F1 score	Harmonic mean of precision and recall	Balanced metric for imbalanced datasets	Ignores true negatives
Classification	ROC-AUC	Model's ability to distinguish classes at different thresholds	Good for binary classification	Not always useful in multiclass settings
Classification	Confusion matrix	Displays TP, FP, TN, FN	Detailed error analysis	Can be hard to interpret without aggregation
Regression	MAE	Mean of absolute errors	Easy to interpret	Ignores error direction and severity
Regression	MSE	Mean of squared errors	Penalizes large errors more	Sensitive to outliers
Regression	RMSE	Square root of MSE	Same unit as target	Same limitations as MSE
Regression	R-square (R^2)	Proportion of variance explained by the model	Measures goodness of fit	Can be misleading for nonlinear models

FN, False negative; *FP*, false positive; *MAE*, mean absolute error; *MSE*, mean squared error; *RMSE*, root mean squared error; *ROC*, receiver operating characteristic; *TN*, true negative; *TP*, true positive.

triggers with unprecedented precision.^{14,15} The AI-based tools can process vast amounts of patient data, including skin prick tests, specific IgE levels, and clinical histories, to identify hidden correlations and predict allergic responses more reliably than traditional diagnostic methods.¹⁶ Moreover, AI facilitates real-time analysis of multi-omics data to uncover novel biomarkers for allergy classification and prognosis.¹⁷

Allergic respiratory diseases

Kavya et al (2021)¹⁸ focused on multidisease allergy diagnosis, using data from 878 patients who visited the clinic undergoing intradermal skin tests. After cleaning, the final sample was 691 for training and 169 for testing, spanning 7 diagnostic categories, including comorbidities like Rhinitis-Urticaria and Urticaria-Others. The authors tested a range of classifiers including Decision Tree, support vector machine (SVM), k-nearest neighbors (k-NN), Neural Networks, and Random Forest. The best-performing model, Random Forest, achieved 83.07% validation accuracy for the Rhinitis-Urticaria comorbidity class. The model was trained using 5-fold cross-validation, and validation included expert assessment of rule-based outputs. The system developed by Ramisetty et al¹⁸ was successfully deployed on mobile platforms, leading to improved diagnostic accuracy in clinical practice: from 77.21% pre-deployment to 81.80% post-deployment. Fu et al (2024)¹⁹ centered specifically on AR and related conditions (eg, sinusitis, chronic rhinitis), analyzing data from 2,231 patients collected over 1 year in Chinese clinics. Their dataset was significantly larger and included multilabel cases (patients with up to 3 coexisting conditions). The authors designed a custom ensemble model called ARF-OOBEE (Adaptive Random Forest—Out-of-Bag—Easy Ensemble). It outperformed other popular algorithms (eg, SVM, Naive Bayes, multi-layer perceptron (MLP), XGBoost) and showed an area under the curve (AUC) of 0.9830, demonstrating the strong generalization and diagnostic potential of their model, particularly for clinical decision support in differentiating AR from similar conditions.¹⁹

Food allergy

In food allergy detection, integrating classic ML with deep learning advancements enabled the identification of intricate molecular patterns essential for accurate allergen prediction. Chennamsetty and Dubey²⁰ used a dataset of 4,854 protein sequences, each described by 31 biochemical features, to predict

allergenicity using ML and deep learning models. The authors tested 13 different algorithms, including ensemble methods, with and without ProteinBERT embeddings, that expanded the feature set to 15,738 dimensions. Validation was performed using fivefold cross-validation, and final performance was evaluated on a separate test set.

On the test set, Voting and Stacking classifiers were top performers, with Voting classifier achieving precision of 96% (nonallergenic), 80% (allergenic), and F1-scores of 93% and 86%, respectively. These results highlight the potential of integrating molecular-level data, such as amino acid embeddings, to significantly enhance allergy prediction accuracy.²⁰

Atopic dermatitis

Two recent studies demonstrated the effectiveness of ML models in diagnosing and evaluating AD using transcriptomic and microbiota data. Jiang et al²¹ analyzed data from 161 children (88 AD patients and 73 controls), developing an SVM classifier that achieved an F1-score of 0.84 using transcriptome-only data and 0.78 when combining microbiota and gene expression. The model was validated on an independent test set ($n = 30$) and identified 35 key genes and 50 microbial taxa as predictive features.²¹ Wu et al²² used 6 public datasets totaling over 400 samples, dividing them into training and test sets (eg, GSE130588 with 96 samples, GSE99802 with 112). Their LASSO and logistic regression models reached AUCs up to 0.88 and showed strong correlations with disease severity (SCORAD scores, $r = 0.55-0.69$). Both studies validated their models across multiple cohorts and consistently identified genes like (*CCL22*) and interleukin-7R (*IL-7R*) as important biomarkers, supporting the potential of ML for precise AD diagnosis and treatment monitoring.²²

IMAGING AND COMPUTER VISION APPLICATIONS IN ALLERGY DIAGNOSIS

Recent advances in computer vision, particularly the use of convolutional neural networks (CNNs), have introduced promising tools for image-based diagnostics in allergic diseases. In the context of allergic conjunctivitis, chronic urticaria and dermatitis, several deep learning models have been developed to automatically assess disease severity from photographs.

Allergic conjunctivitis

Two recent studies significantly expand the application of AI in ocular allergy diagnosis and monitoring. Yarin et al (2023)²³ present the development and validation of AllergoEye, an AI-based software platform for objectively quantifying allergic reactions during conjunctival provocation tests. Notably, AllergoEye's objective scores showed a stronger correlation with patients' serum specific IgE levels than traditional Summation Symptom Score–based assessments. This suggests that AI-enhanced conjunctival provocation tests could provide more reliable, quantitative biomarkers for both diagnosis and therapy in allergic conjunctivitis.²³ Recently, Yonehara et al²⁴ showed that the AI model achieved high diagnostic accuracy (86.2%), significantly outperforming nonspecialist ophthalmologists (60.0%), with AUC greater than 0.8 for most disease categories, demonstrating that explainable deep learning models can not only match but also exceed human performance in diagnosing complex ocular allergies while also offering transparent reasoning that can support real-world clinical use.

Chronic spontaneous urticaria

A recent study introduces a novel deep learning–powered system for automatically assessing chronic spontaneous urticaria severity, a skin condition characterized by recurrent hives that can be difficult to quantify manually. Despite variability in hive appearance, especially in severe cases in which lesions were numerous, overlapping, or irregularly shaped, the model performed comparably with human specialists in hive counting (F1 ~0.62). In conclusion, the study shows how AI can bring objectivity, consistency, and scalability to the diagnosis and monitoring of cutaneous allergic diseases.²⁵

Contact dermatitis

One study recently introduced a promising ML application for allergic contact dermatitis. The researchers developed and evaluated a CNN that achieved remarkably high accuracy (99.5%) and a strong F1-score (0.89) in identifying positive versus negative reactions in epicutaneous patch testing.²⁶

In a prospective trial, 206 participants underwent standardized patch testing with 10 allergens. Five days post-application, site photographs were analyzed by both the AI model and human readers, with clinical assessments by board-certified dermatologists serving as the reference standard. The ML model demonstrated strong overall performance, with AUC of 0.86, suggesting that deep learning can support accurate and accessible contact dermatitis diagnosis using smartphone-captured images, which could represent promising tools for remote or point-of-care applications.²⁷

Drug allergy

Drug allergies represent a significant challenge in modern health care. They are unpredictable, often severe, and notoriously difficult to diagnose. Although detailed clinical history and confirmatory tests remain the bedrock of diagnosis, their subjectivity, variability in practice, and potential risks (especially in provocation testing) leave much room for improvement. The AI is a field that promises not only to enhance diagnostic accuracy but also to revolutionize the approach to drug hypersensitivity through data-driven insights.¹⁵ Recently, a study showed that ML models demonstrated high levels of accuracy in the classification and risk stratification of penicillin-adverse drug reaction.²⁸

AI-DRIVEN ENDOTYPING AS A BRIDGE BETWEEN DIAGNOSIS AND PERSONALIZED THERAPY

In allergic diseases, in which heterogeneous clinical presentations often obscure therapeutic responsiveness, AI-based endotyping provides a critical bridge between diagnosis and precision treatment.

By integrating multi-omics data (eg, transcriptomics, proteomics, metabolomics) with clinical features, ML models can uncover underlying disease mechanisms and stratify patients into endotypes that are predictive of treatment response.²⁹ For instance, in severe asthma, AI-assisted clustering of molecular profiles has revealed T2 helper (T2)-high and T2-low endotypes, which directly inform the use of biologics such as anti-IL-5 or anti-IgE therapies.³⁰ Similar approaches are emerging in AD and AR.^{10,11} These AI-driven insights not only enhance diagnostic precision but also support therapeutic decision making, aligning specific biological pathways with targeted treatments. Thus, AI serves as a central component in realizing the goals of precision medicine, moving from phenotype-driven trial-and-error approaches to mechanism-based, individualized therapy selection.

Personalized treatment plans

The AI and ML are rapidly advancing the standard of care in allergy, enabling clinicians to move from generalized treatment protocols to precision, individualized care. By integrating data from genomics, clinical history, environmental exposures, and patient-reported outcomes, AI can help design more effective, patient-centered treatment plans across both adult and pediatric populations.³¹⁻³⁴

Personalized treatment selection for respiratory allergy.

Biologic therapies targeting IgE and T2 inflammatory pathways have revolutionized treatment for moderate-to-severe asthma and chronic rhinosinusitis with nasal polyps (CRSwNP). However, selecting the optimal biologic and the length of use is challenging owing to patient heterogeneity. The AI tools can help identify ideal candidates for these biologic therapies by analyzing clinical and molecular profiles.^{32,33} The AI also excels at processing high-dimensional omics and environmental data. The ML clustering has defined new asthma endotypes—such as patients with neutrophilic, non-T2 inflammation—who may not benefit from eosinophil-targeting biologics.³³ In one real-world dataset of over 3,000 asthma patients, AI models predicted outcomes after discontinuing biologics with AUC values of approximately 0.72 to 0.74, indicating moderate discriminative ability. In clinical terms, this level of accuracy may support shared decision making around tapering by flagging patients who are more likely to maintain disease control after discontinuation and those at higher risk of relapse. Although not definitive, such models can complement clinician judgment and help guide more personalized biologic stewardship.³³

The management of AR and CRSwNP increasingly demands individualized strategies that account for patient-specific disease trajectories, comorbidities, and treatment responses. The AI, particularly ML, offers a transformative opportunity to support such precision medicine approaches.

In AR, long-term success with allergen immunotherapy (AIT)—specifically subcutaneous immunotherapy (SCIT)—is highly dependent on patient adherence. Li et al³⁵ introduced

sequential ML models, including long short-term memory (LSTM) networks and stochastic latent actor-critic (SLAC) frameworks, to predict both adherence and symptom trajectory in patients undergoing SCIT. These models use time-series data from clinical visits, including visual analog scale symptom scores and medication use, as well as demographic and immunological markers such as total IgE and eosinophil levels. The predictive accuracy of these models (66%–84% for LSTM) underscores their potential to enable real-time clinical decision support, identifying patients at risk of dropout and allowing for timely, personalized intervention strategies to enhance therapeutic success.

In CRSwNP, the application of ML extends beyond adherence to outcome prediction following endoscopic sinus surgery. Gata et al³⁶ developed a Random Forest model trained on preoperative clinical data—such as endoscopy scores, Sino-Nasal Outcome Test-22 (SNOT-22), blood eosinophilia, and even epigenetic markers like miR-125b—to predict postoperative disease control, partial control, or relapse with up to 84.62% accuracy. The incorporation of molecular data significantly enhanced prediction performance, indicating the importance of multidimensional inputs, including inflammatory endotypes, in guiding treatment selection. This enables more accurate counselling, risk stratification, and selection of candidates for adjunctive biologic therapies or alternative surgical strategies.

Complementing these findings, Sima et al³⁷ explored biomarker-based prediction of response to omalizumab, an anti-IgE monoclonal antibody, in patients with refractory CRSwNP comorbid with asthma. Using receiver operating characteristic analysis, serum CCL-3, CCL-4, and IL-8, as well as nasal secretion markers like C-X-C Motif Chemokine Ligand 1 (CXCL-1) and granulocyte-macrophage colony-stimulating factor, demonstrated strong predictive value for clinical improvement in SNOT-22 and nasal congestion scores. These biomarkers may serve as AI-compatible input features for algorithmic models aimed at optimizing biologic treatment decisions, helping clinicians predict which patients will benefit most from omalizumab.

Together, these studies underscore the promise of AI in moving beyond population-level treatment guidelines toward nuanced, patient-specific care in allergic airway diseases. By integrating clinical, behavioral, and molecular data, AI models can facilitate personalized treatment planning, improve adherence, predict outcomes, and ultimately improve quality of life for patients with AR and CRSwNP.

AI-enabled personalized treatment in cutaneous allergic disease. The AD represents a clinically heterogeneous, inflammatory skin disorder with variable treatment response to systemic therapies. As novel biologics and small molecules expand the treatment landscape, ML has emerged as a key tool to support personalized treatment selection by identifying predictors of therapeutic response or failure.

In a real-world study using electronic health records (EHRs) and claims data, Wu et al³⁸ applied multiple ML models—including Random Forests and Gradient Boosted Trees—to identify predictors of nonresponse to dupilumab, a monoclonal antibody targeting IL-4 and IL-13 signaling, in AD patients aged 12 years or older. Among the 419 patients analyzed, 35% experienced at least 1 indicator of nonresponse, such as treatment discontinuation, need for additional systemic therapies, or

incident skin infections. The ML models identified key predictors of nonresponse, such as prior ibuprofen use, higher comorbidity burden (Quan-Charlson Index), female sex, and psychiatric comorbidities. These insights highlight how ML can be harnessed to guide risk stratification and enable proactive management strategies for patients at risk of treatment failure.

Complementary to this, Thyssen et al³⁹ used a classification and regression tree model to explore baseline predictors of response to baricitinib, a Janus kinase 1/2 inhibitor, in adults with moderate-to-severe AD enrolled in a phase 3 trial. The model identified baseline body surface area involvement and itch severity as the most predictive variables. Patients with body surface area between 10% and 40% and high itch scores (numeric rating scale ≥ 7) had the highest likelihood of achieving both the Eczema Area and Severity Index-75 (EASI-75) and a 4-point or greater improvement in itch at week 16. This analysis supports the use of ML tools to define clinically relevant AD subtypes—such as the “itch-dominant” phenotype—and to tailor therapy accordingly.

Beyond predicting response to approved treatments, Fortino et al⁴⁰ utilized ML algorithms for biomarker discovery in skin diseases, including AD, based on transcriptomic data. Their model, trained on public gene expression datasets, identified differentially expressed genes and signaling pathways relevant to disease activity and treatment targets. Such approaches may soon enable integration of omics data into decision support tools, allowing dermatologists to select therapies based not only on clinical phenotype but also on molecular endotypes.

In chronic spontaneous urticaria, a 2021 study applied ML techniques to predict patient response to omalizumab based on clinical and demographic data.³⁴ The ML models such as SVM and k-NN* were trained on features including IgE levels, D-dimer, and C-reactive protein.³⁴ These models demonstrated reasonable accuracy and could identify early, late, and non-responders to therapy. This approach may enhance clinical decision making by predicting who will benefit most from treatment and when.

Together, these studies demonstrate the growing value of AI in cutaneous allergic diseases. By analyzing large-scale real-world or trial datasets, ML models can uncover patterns in patient characteristics, biomarkers, and treatment outcomes that are otherwise difficult to detect, offering a pathway toward precision dermatology.

FOOD ALLERGY AND ML

A study on milk oral immunotherapy used ML and epitope-specific IgE profiling to predict which patients would develop sustained unresponsiveness after discontinuing therapy. Researchers analyzed antibody binding to 66 milk protein epitopes in 47 patients and found that lower baseline IgE binding to specific epitopes strongly predicted sustained unresponsiveness outcomes. An elastic net ML model using just 6 informative IgE-binding epitopes achieved 87% accuracy and an AUC of 0.95.⁴¹ These findings suggest that epitope-level analysis could outperform standard IgE component testing in predicting long-term oral immunotherapy success, paving the way for more personalized food allergy care. However, given a relatively small sample size ($n = 47$) for generalization, these are preliminary findings and there is a need for further validation.

MOBILE APPS, WEARABLES, AND DIGITAL SUPPORT TOOLS

The AI is increasingly integrated into allergy management through mobile apps, wearables, and digital decision support tools. These technologies enable real-time symptom tracking, environmental exposure monitoring, and personalized treatment adjustments making allergy care more proactive, data-driven, and patient-centered.

Environment-responsive interventions

The AI-based mobile apps can correlate real-time environmental data (eg, pollen, pollution, humidity) with patient symptoms and suggest preemptive steps like increased inhaled corticosteroids or antihistamines. Pediatric patients are especially likely to benefit from such proactive care.^{31,42}

The AIT—including subcutaneous, sublingual, and oral routes—can be tailored using AI. Traditionally guided by skin prick tests and serum IgE levels, AIT can now incorporate data from clinical history, component-resolved diagnostics, and environmental exposures.^{33,42}

For environmental allergy, an AI-assisted clinical decision support system, called @IT-2020, was used to help clinicians manage AR and asthma by integrating real-world patient data with evidence-based guidelines. The @IT-2020 integrates pollen data, symptom profiles, and sensitization patterns to generate guideline-aligned AIT recommendations.⁴² This is especially valuable for polysensitized patients, in whom AI can prioritize allergens and recommend treatment duration and type.

Although direct head-to-head comparisons with clinician judgment are limited, early studies suggest @IT-2020 enhances adherence to Allergic Rhinitis and its Impact on Asthma (ARIA) guidelines and improves decision-making consistency, particularly in complex cases. Further research is needed to fully assess its comparative performance and real-world impact.

Mobile health, wearables, and real-time monitoring

Smart inhalers and mobile health (mHealth) tools can track symptoms, medication use, peak flow, sleep, and physical activity. The ML algorithms detect signs of poor control or early exacerbations. Some digital inhalers now predict asthma attacks and prompt timely interventions.³³

The MASK-air app, used worldwide, aggregates AR symptoms and treatment behaviors to provide real-world insights into medication adherence and effectiveness.⁴²

The KeepSmilin4Abbie Foundation has used mobile AI tools to help manage food allergy risk and issue anaphylaxis alerts, showcasing how AI can be life-saving and scalable.³¹

At present, most U.S. Food and Drug Administration—cleared AI tools are “locked” models that do not change after approval. Whereas some systems include mechanisms for ongoing performance monitoring, real-time adaptive learning and validation remain an evolving area under regulatory development.

Psychosocial tailoring and patient engagement

The AI can also address behavioral and emotional factors. Adolescents who forget auto-injectors or medications can be flagged by usage data. The AI systems can respond with personalized motivational messages or caregiver alerts.⁴²

Chatbots powered by large language models can provide tailored coaching and education. For example, AI can guide

patients through immunotherapy initiation, explain side effects, or offer emotional support—adapted to their literacy level and psychological readiness.³³

This is especially impactful in pediatric care, where apps with gamified reminders or epinephrine simulations boost self-efficacy and reduce anxiety.⁴²

AI-DRIVEN PREDICTIONS FOR PROACTIVE MANAGEMENT

The AI has transformative potential in proactively managing allergic diseases. Beyond diagnosis and treatment of existing illness, AI-powered predictive systems can identify at-risk populations, enhance preventive strategies, and (in cases of established illness) anticipate disease flares. This proactive approach helps accelerate the transition from reactive management to predictive and preventive medicine.

Early identification of at-risk populations

The AI-based models trained on birth cohort data, genomic profiles, and environmental exposures can be leveraged to identify individuals at increased risk of developing allergies, asthma, and AD. Predicting the development of these conditions before clinical manifestation is a critical opportunity for primary prevention of chronic allergic diseases, particularly asthma. He et al⁴³ demonstrated the ability of ML algorithms to predict childhood asthma development using data from birth cohorts, identifying early-life risk factors that may contribute to disease onset. Other AI models analyzing the combination of gene expression and clinical data have been employed to predict asthma susceptibility, highlighting potential molecular pathways for preventive strategies.⁴⁴ The AI also has the potential to identify novel risk factors for disease development that can augment allergists' predictive capabilities. Liu et al⁴⁵ investigated the ability of an ML model to predict future chronic lung disease (asthma and chronic obstructive pulmonary disease) based on gut microbiome, finding it to have higher predictive performance than conventional risk factors alone. Combining microbial taxa abundance with known risk factors further strengthened the model's predictive capacity. Early identification of at-risk cohorts using the aforementioned models can facilitate targeted actions, such as proactive initiation of AIT in high-risk toddlers showing early sensitization to aeroallergens—children who might otherwise receive counseling on environmental allergen control and medications alone.

Environmental and allergen exposure forecasting

The AI models integrating real-time environmental data have shown promise in predicting allergen exposure levels and guiding preventive care. Predictive algorithms that process meteorological data, pollen concentrations, air pollution, and geolocation inputs are being applied to generate exposure risk maps. Zhong et al⁴⁶ utilized multimodal ML models (radar imagery, wind speed, air temperature, and the normalized difference vegetation index) to forecast pollen concentrations, offering insights for managing seasonal AR. Such models enable proactive adjustments to treatment plans, particularly during peak pollen seasons or in high-risk geographic areas where manual pollen counting is not practical. Furthermore, AI systems analyzing environmental monitoring data are being developed to predict population-based asthma exacerbations based on local air quality and climatic conditions. Hwang et al⁴⁷

demonstrated that a recurrent neural network integrating such datasets enhances prediction accuracy and can aid policy makers in their efforts to understand and mitigate environmental impacts on asthma exacerbations. Based on AI-enabled forecasting, clinicians can preemptively advise patients to limit outdoor activity, increase air filtration, and initiate or step up controller therapies several days before peak exposure. This proactive strategy, aligned with guideline-based anticipatory treatment, has the potential to reduce symptom severity and prevent asthma exacerbations and minimize emergency health care utilization.

Prediction of disease exacerbations and remission

The AI models are increasingly employed to predict both disease exacerbations and remission, particularly in chronic respiratory and dermatological conditions. In asthma, ML models have demonstrated accuracy in predicting exacerbations, emergency department visits, and hospitalizations. Zein et al⁴⁸ were able to accurately predict pediatric asthma exacerbations with an ML algorithm trained on outpatient demographics, comorbidities, laboratory values, and medications. Such models can be utilized to target “just in time” interventions (such as remote physiological monitoring, proactive outpatient evaluation, and step-up controller therapy) toward those patients most likely to develop exacerbations, potentially reducing systemic steroid burden and tertiary care utilization. Conversely, AI-driven analytics can also be helpful in predicting resolution or remission of chronic allergic disease. Bose et al⁴⁹ developed multiple ML models to differentiate between children with early-life asthma diagnoses who would and would not go on to have persistent asthma symptoms beyond 5 years of age. Similarly, Pivneva et al⁵⁰ identified multiple demographic and clinical variables that could be analyzed by an ML algorithm to successfully predict time from diagnosis to remission for adult patients with chronic urticaria. Being able to more accurately predict remission of these chronic illnesses can help inform counseling and shared decision making when it comes to treatment decisions (eg, AIT or biologics).

Integrating predictive analytics into clinical decision support systems

Incorporating predictive AI models into clinical decision support systems holds substantial potential for enhancing preventive care. These systems can generate alerts for clinicians when patients are at elevated risk of exacerbation or sensitization based on predictive analytics. Embedding such tools within EHR systems can prompt timely intervention, guide medication adjustments, or recommend preventive strategies before clinical deterioration occurs. One such example is in the prediction of drug allergies. Moreno et al⁵¹ used retrospective data from patients evaluated for β -lactam allergy to construct a predictive artificial neural network and found it to be superior to logistic regression at predicting β -lactam allergy. In settings in which penicillin skin testing and desensitization may not be available in a timely manner, integration of similar AI-powered predictive models into clinical decision support systems has the potential to minimize hypersensitivity reactions and optimize antimicrobial stewardship. For example, these models could be embedded as a dynamic module within the medication order entry system, where the AI algorithm provides the clinician with a calculated probability of IgE-mediated β -lactam allergy. Based on

institutional protocols, the system can then recommend a 2-step graded drug challenge or suggest therapeutic alternatives as appropriate.

Research gaps, implementation challenges, and future directions

Despite promising advances, challenges remain. Data heterogeneity, lack of generalizability, and inconsistent model explainability continue to hinder widespread implementation of predictive AI systems. In addition, most predictive models require prospective validation in real-world clinical settings to demonstrate robustness and utility. Furthermore, there are practical barriers to broad implementation of predictive AI systems, which include variable access to digitized data on which to train models, regional differences in data standards impacting the scalability of AI models across the globe, and the cost of integration into public health systems that already suffer from chronic underfunding. Future research should integrate multimodal data sources, including EHRs, genomic data, environmental factors, and wearable devices, to enhance predictive accuracy. Special attention should be given to underserved populations and pediatric cohorts, in whom early identification and intervention may offer the greatest benefits. Addressing these gaps will be essential to fully realize the potential of AI-driven predictive models in allergy and immunology, but will require collaboration across silos of expertise. Multidisciplinary cross-regional working groups including clinicians, epidemiologists, data scientists, bioinformaticians, ethicists, implementation specialists, and patient-centered stakeholders can align priorities and provide recommendations on how to allocate limited resources.

ENHANCED PATIENT ENGAGEMENT AND SUPPORT

Patient engagement

By leveraging technologies like natural language processing, ML, and conversational AI, health care providers are transforming how they connect with patients, ensuring personalized, efficient, and impactful communication.⁵² The AI plays a pivotal role in addressing the challenge of patient engagement, which has long been considered the “last mile” problem in health care. Studies show that engaged patients tend to adhere to treatment plans, attend appointments, and make better health decisions. However, maintaining this engagement requires consistent effort and resources—areas in which AI excels.⁵³ The AI-powered chatbots are best positioned for use in preclinical settings—such as initial symptom triage, health information dissemination, or patient education—and should not be relied upon for diagnostic decision making, which remains the responsibility of qualified health care professionals.

Key applications of AI in patient engagement

Virtual assistants and chatbots. The AI-driven chatbots can provide 24 hours a day, 7 days a week support, answering nonclinical and administrative questions that can oftentimes hold up care. These tools can reduce the burden on health care staff and limit back-and-forth relating to appointment scheduling and availability, prescription refills, insurance coverage, and status of prior authorizations.^{54,55}

Appointment scheduling and reminders. The AI automates scheduling processes, sends reminders, and can serve up providers that are aligned with patient preferences, saving

patients time reviewing individual clinician profiles. This can improve accessibility, completed initial appointments, and reduce missed appointments.⁵²

Personalized communication. The AI can tailor messages to the tone, style, and cultural competency standards preferred by each patient, enhancing understanding and adherence to care plans.⁵² The AI can also be leveraged for medication management through automated reminders and reduce noncompliance. It can also troubleshoot pharmacy and issues such as changing a pharmacy location or coverage challenges.⁵²

Health goal tracking

The AI can monitor patient progress toward health goals by analyzing data from wearable devices or EHRs and provide actionable insights. This would take substantial staff time and, therefore, it reduces the burden of staffing.⁵⁵ With a projected shortage of up to 48,000 primary care physicians by 2034 in the United States, AI offers solutions to alleviate the workload of clinicians while maintaining high levels of patient engagement. By automating repetitive and administrative tasks such as follow-up communications, medication adherence, and adherence to care plans, clinicians can operate at the top of their license.⁵⁶ However, although AI offers transformative benefits, its implementation must address ethical concerns such as data privacy, algorithmic bias, and the potential erosion of human interaction in health care. Ensuring that AI complements rather than replaces human relationships is essential for fostering trust and empathy within patient-provider interactions.⁵⁴

PATIENT ENGAGEMENT IN ALLERGY

The AI has specific uses for patient engagement in the field of Allergy. The AI-powered chatbots, such as ChatGPT (generative pretrained transformer) 4.0, are being used in allergies to provide patients with real-time assistance and education for general allergy questions, mostly prior to establishment of the doctor-patient relationship so as to not be misconstrued as direct medical advice. These chatbots can answer common questions about AIT or other treatments and provide general guidance on managing symptoms or adverse events.⁵⁷ For example, a chatbot can explain how AIT differs from symptomatic allergy medications by emphasizing its long-term benefits and disease-modifying effects. This helps patients make informed decisions about their care and come prepared to discuss options with their provider.⁵⁷ In addition to health education, AI has specific uses for allergy and asthma including updates on outdoor allergen levels, symptom monitoring and management, immunotherapy adherence, and patient support.⁵⁸ One of the biggest challenges is ensuring adherence to long-term treatments such as SCIT. Poor adherence often stems from a lack of understanding about the treatment or its side effects, or challenges related to scheduling. The AI can address these issues by providing proactive information in advance of immunotherapy appointments, using predictive analytics to identify patients at risk of noncompliance based on behavioral patterns or past data, and sending personalized “push” notifications through apps or text messages to remind patients of upcoming doses or appointments.^{56,59} Looking forward, AI-powered platforms can analyze patient data from wearables or EHRs to predict asthma exacerbations, allowing for preemptive action that keeps patients engaged in their care.⁵⁹ The AI-driven

remote monitoring devices can collect data on symptoms, medication use, and environmental triggers, which can then be analyzed using ML algorithms. This enables real-time feedback for patients on their condition, alerts for health care providers when intervention is needed, and enhanced communication between patients and providers during visits.

CHALLENGES AND ETHICAL CONSIDERATIONS

Incorporating AI into health care poses many challenges that must be considered to ensure the safety, equity and integrity of continued high-quality care of our patients.

Bias in data

The AI outputs are only as unbiased as their training data. Medical datasets are riddled with our own biases, societal biases and individual provider biases, that often reflect historic disparities and structural inequities in health care.⁶⁰ Underrepresented populations may have less robust data given decreased access to health care, which can impact algorithmic performance.⁶¹ In addition, inherent biases can be further amplified when used by an algorithm, one well-described case was from Obermeyer et al,⁶² who unveiled racial bias in an algorithm intended to improve care support for complex patients. The algorithm used historic health care cost as a proxy to predict an individual’s need for health care. However, owing to cultural and socioeconomic reasons, Black patients had less health care cost due to less usage, and thus, the algorithm consistently underestimated illness severity for Black patients. The American Medical Informatics Association (AMIA) has developed guidelines recommending “transparency labels that describe the purpose of the AI tool, the population on which the data was trained, and mandating testing in diverse user populations during development to address equity.”⁶³ Two transparency label examples are shown in Figure 2, one for any generative AI tool and another for a specific sepsis management tool. These labels help physicians to assess when to use these AI tools, like reviewing population characteristics in randomized control trials to determine generalizability to their own patients.

Hallucination and accuracy concerns

Although AI does hallucinate, creating instances in which it appears to have created accurate outputs but is factually incorrect, these instances are decreasing overall as AI continues to advance. Nonetheless, one cannot blindly accept AI, and thus, understanding how a model generates its conclusions is a key focus of newer tools. Although ChatGPT provided accurate or somewhat accurate responses to 91% of common allergy myths in one study,⁶⁴ GPT-based chatbots were frequently inaccurate for other conditions like eosinophilic esophagitis.⁶⁵ Linking evidence directly to the output improves the ability of physicians to validate sources within medical records. However, many systems remain a “black box”, with limited understanding of the decision-making process. Health care applications demand AI that clearly explains how conclusions are reached, what factors are considered, and what uncertainties there are in the recommendation.

The physician impact

The AI implementation profoundly affects physician practice patterns and cognitive processes. Automation bias, in which physicians over-rely and agree with AI recommendation, has been

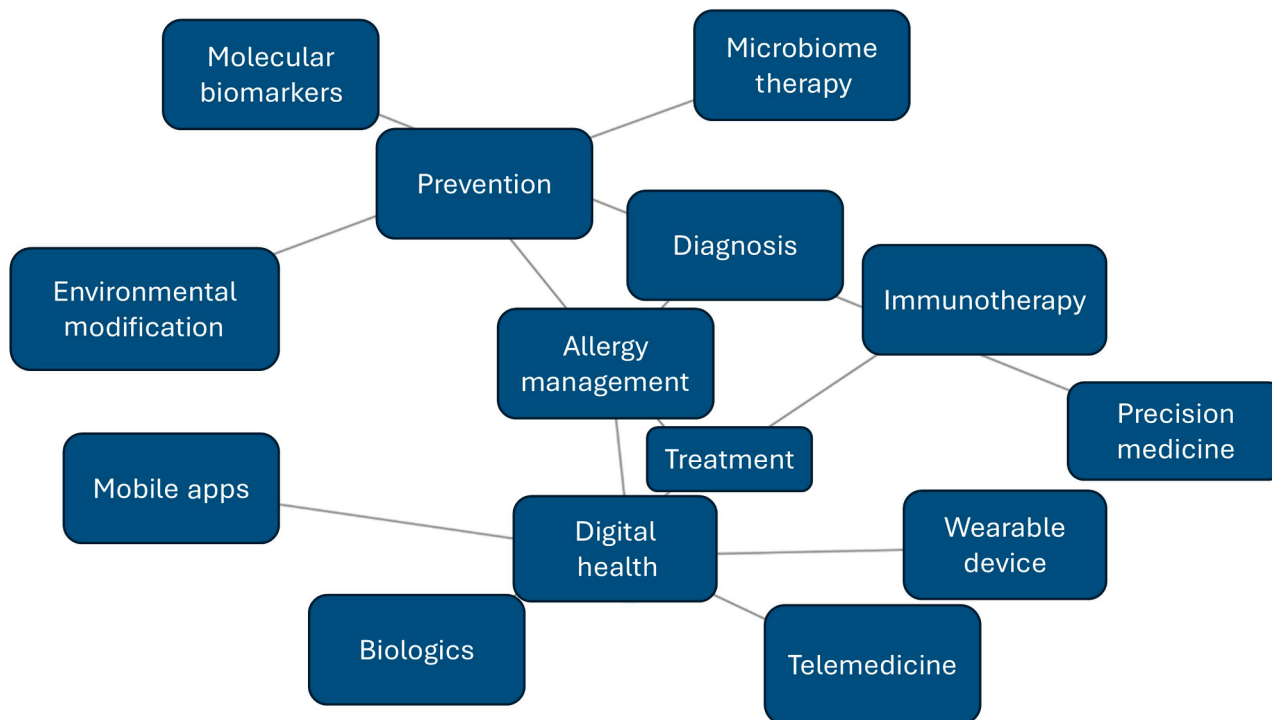


FIGURE 3. Conceptual map of allergy management advancement.

to up to \$600 per month per provider. Not all AI tools are equal, and the more rigorously studied and proven systems can be cost-prohibitive to smaller practices. The ability to scale evidence-based AI tools to rural and smaller practices must be considered. Rural, elderly, and socioeconomically disadvantaged patient populations also lack access to devices, connectivity or the digital literacy required for AI-supported care.⁷¹ As AI becomes increasingly embedded in health care delivery, failing to address the digital divide may worsen existing disparities, undermining the very efficiency gains such systems promise.

Ethical and legal considerations

Who is responsible when AI systems give false information, and harm is done to a patient, represents a significant legal challenge. Current frameworks inadequately address whether liability rests with developers, implementing institutions, or the clinicians using these tools. The AMIA emphasizes that accountability should be on the organizations that are developing, deploying, and maintaining the AI system.⁷¹ With the evolving technology landscape, significant cybersecurity risks are also present. To study and utilize these new tools requires access to sensitive patient data, creating many potential breach points. Ensuring that each tool follows appropriate legal requirements for privacy is paramount. Patient consent presents another ethical consideration. Notably, 6 out of 10 patients do not trust the use of AI in their health care.⁶³ This brings up questions such as whether patients should be explicitly informed when AI influences their care. Regulatory frameworks are struggling to keep pace with the implementation of AI. Whereas the U.S. Food and Drug Administration’s Digital Health Center of Excellence has established approval pathways for certain AI medical devices, broader governance and monitoring remains fragmented.

CONCLUSIONS

The management of patients with allergic diseases is undergoing a paradigm shift driven by advancements in precision medicine and digital health technologies (Figure 3).

Digital health technologies are also playing an increasingly critical role in allergy management. Mobile health applications, wearable biosensors, and telemedicine platforms provide real-time monitoring of symptoms and medication adherence, enhancing patient engagement and clinical decision making. These tools hold the potential to bridge gaps in health care accessibility and facilitate continuous disease management outside clinical settings.

Despite these advancements, challenges remain in ensuring equitable access to novel therapies and integrating emerging technologies into routine clinical practice. Ethical considerations, regulatory frameworks, and health care disparities must be addressed to maximize the benefits of these innovations. Future research should focus on multidisciplinary approaches that incorporate genetic, environmental, and immunological insights to refine precision allergy management.

Whereas most AI applications in allergy have concentrated on drug hypersensitivity, respiratory allergies, and skin-related conditions, key areas like insect venom allergies (such as sting-induced anaphylaxis) and eosinophilic disorders (such as eosinophilic esophagitis) remain largely unexplored. Expanding research in these fields offers a valuable opportunity to extend the clinical reach of AI-powered diagnostic tools.

The improved diagnostic accuracy demonstrated by the AI model has direct clinical implications. In allergy clinics, such tools could support earlier and more reliable diagnosis, especially in settings with limited access to subspecialists. By reducing observer-dependent variability and standardizing interpretation,

AI may help clinicians stratify patients more accurately and initiate appropriate interventions sooner, ultimately improving patient outcomes and optimizing resource use.

In conclusion, the future of allergy practice will be characterized by a shift toward personalized medicine, leveraging cutting-edge technologies to improve diagnostic accuracy, treatment efficacy, and patient outcomes. The AI-driven tools have the potential to integrate vast amounts of patient data, including genetic, immunological, and environmental factors, to provide clinicians with actionable insights that can improve patient outcomes and reduce the burden of allergic diseases on health care systems. As scientific understanding continues to expand, collaborative efforts across research, clinical practice, and health care policy will be essential in shaping the next generation of allergy therapeutics and preventive strategies.

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