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Role of Artificial Intelligence in Disease and Pest Management in Cauliflower: A Review

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This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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Review Article

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Abstract

Cauliflower (*Brassica oleracea* var. *botrytis* L.) is a nutritionally important cole vegetable and a high-value component of intensive vegetable production. Its yield and market quality are frequently reduced by bacterial, fungal and oomycete diseases and by insect pests that cause direct feeding injury or facilitate secondary infections. Conventional disease and pest surveillance is largely dependent on visual scouting, expert diagnosis and periodic field observations. These approaches remain indispensable, but they can be labour-intensive, subjective and difficult to scale over large production areas. Artificial intelligence (AI), including machine learning, deep learning, computer vision, image segmentation, object detection, remote sensing and predictive analytics, offers a complementary approach for rapid and repeatable crop-health assessment. This review examines the potential role of AI in cauliflower disease and pest management, covering image acquisition, disease classification, lesion localisation, severity estimation, insect identification, automated counting, forecasting, smartphone applications, UAV-based surveillance and AI-enabled integrated pest management. Cauliflower-specific research has demonstrated promising performance of deep-learning models. The Cauli-Det modified YOLOv8 system reported precision of 93.2%, recall of 82.6% and mean average precision of 91.1% for bacterial soft rot, downy mildew and black rot in its experimental dataset (Uddin *et al*., 2024). Another recent cauliflower study reported 99.85% classification accuracy using EfficientNet-B3 under its experimental conditions (Malik *et al*., 2025). Broader plant-disease research also demonstrates strong potential for CNNs and transfer learning (Mohanty *et al*., 2016; Ferentinos, 2018), while pest-detection research supports automated insect recognition and monitoring (Thenmozhi & Reddy, 2019; Chakrabarty *et al*., 2026). However, field variability, limited crop-specific datasets, class imbalance, symptom similarity, model explainability, computational

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requirements and inadequate independent validation remain major constraints. Future research should integrate AI predictions with weather, crop stage, pest abundance, disease severity and economic thresholds so that the technology supports practical, affordable and environmentally responsible IPM in cauliflower.

Keywords: Artificial intelligence; cauliflower; machine learning; deep learning; computer vision; disease detection; insect pest detection; image segmentation; precision agriculture; integrated pest management.

1. Introduction

Cauliflower is one of the major cole vegetables cultivated for its immature inflorescence, commonly referred to as the curd. The crop is sensitive to environmental fluctuations and is exposed to a broad range of biotic stresses during nursery, vegetative and curd-development stages. Diseases can reduce plant establishment, leaf area, curd quality and marketability, whereas insect pests may cause defoliation, sap loss, contamination and direct damage. The management problem is therefore both biological and operational: farmers must identify the correct causal agent at the right time and select an intervention appropriate to the intensity and economic importance of the problem.

Traditional diagnosis is based on symptoms, signs, field history and, where necessary, laboratory confirmation. Visual scouting is particularly valuable because trained plant pathologists and entomologists can integrate information that is difficult for an image model to capture. Nevertheless, manual monitoring over large areas requires considerable labour and may not provide sufficiently frequent observations. Similar-looking symptoms can also result from different pathogens, nutrient disorders, chemical injury or environmental stress. These limitations have stimulated interest in digital agriculture and AI-assisted crop-health assessment. Recent assessments indicate that AI-enabled crop surveillance can supplement periodic scouting by combining image observations with sensor-derived information, although field validation remains necessary before model outputs inform management (Sial *et al*., 2026).

Artificial intelligence refers to computational approaches that enable machines to perform tasks associated with learning, recognition, prediction and decision support. In agriculture, machine learning can analyse structured environmental or crop data, while deep learning can learn complex features directly from images and other high-dimensional data. Reviews have documented rapid growth of AI applications in agriculture, especially for plant disease recognition and precision management (Kamilaris & Prenafeta-Boldú, 2018; Sajitha *et al*., 2024). A recent review of convolutional neural network applications identifies field-representative images, interpretability and deployment constraints as important considerations for practical plant-disease monitoring (Oktaviani *et al*., 2026). Broader evidence on deep-learning approaches likewise highlights the need to assess classification, detection and segmentation methods under variable field conditions (Shoaib *et al*., 2025).

The significance of AI for cauliflower is not simply the possibility of achieving high classification accuracy. A practically useful system should provide information that can be converted into a crop-protection decision. For example, an image model may detect black-rot-like symptoms, localise the affected area and estimate severity; the decision layer can then combine severity with crop stage, weather and field history to determine whether intensified scouting or management is warranted. This review therefore considers AI as part of a broader decision-support system rather than as a standalone diagnostic substitute. A recent survey of plant-leaf disease recognition emphasizes dataset diversity and the applicability of deep-learning approaches beyond controlled settings (George *et al*., 2025). Research on vegetable-disease detection also identifies variable illumination and target occlusion as challenges for image-based recognition (Liu *et al*., 2025).

Despite progress in image-based crop-health assessment, a practical gap remains between detecting a disease or pest and using that information to guide cauliflower management according to severity, pest abundance, crop stage and action thresholds. Field validation and integration with established integrated pest management practices therefore require specific consideration.

The objective of this review is to examine the applications and limitations of artificial intelligence in cauliflower disease and insect-pest management, focusing on image-based detection, localisation, severity estimation, pest identification and counting, forecasting, and integration with field-validated integrated pest management decision support.

2. Important Diseases and Pests of Cauliflower

Cauliflower is affected by diseases caused by bacteria, fungi and oomycetes (Tripathi *et al*., 2024). Black rot, caused by *Xanthomonas campestris* pv. *campestris*, is a major bacterial disease of cruciferous vegetables and can produce characteristic chlorosis and necrosis. Downy mildew can develop under favourable moisture and temperature conditions, while bacterial soft rot can rapidly destroy tissues and reduce market quality. Brassica disease management is complicated by pathogen survival, contaminated seed or planting material, crop residues, volunteer plants and conducive environmental conditions (Gupta *et al*., 2013; Greer *et al*., 2023).

The insect complex includes aphids, diamondback moth, cabbage butterfly and several caterpillar species. Their damage patterns differ according to feeding behaviour and developmental stage. Aphids may form colonies and cause curling or chlorosis, whereas chewing larvae produce holes, skeletonisation and defoliation. A computer-vision model therefore needs to recognise both the insect itself and, in some applications, the characteristic damage it produces.

Table 1. Major diseases and insect pests of cauliflower and their potential targets for artificial intelligence-based detection, classification, monitoring and management

Category	Examples	Potential AI target
Bacterial diseases	Black rot; bacterial soft rot	Classification, lesion localization, severity
Oomycete disease	Downy mildew	Classification, lesion detection, risk prediction
Other diseases	Damping-off and rot complexes	Nursery/field image screening
Sucking pests	Aphids	Detection, counting, colony mapping
Defoliators	Diamondback moth, cabbage butterfly	Larval/adult detection, counting
Caterpillar complex	Spodoptera and related larvae	Object detection, damage estimation
Mixed problems	Disease + pest + abiotic stress	Multi-class diagnosis and decision support

3. Artificial Intelligence Technologies Relevant to Cauliflower

3.1 Machine Learning

Machine-learning algorithms learn relationships between input variables and outcomes from labelled or unlabelled observations. Support Vector Machines, Random Forests, decision trees, k-nearest neighbours and artificial neural networks can be applied when meaningful features are available. For cauliflower protection, inputs may include temperature, relative humidity, rainfall, leaf wetness, crop age, disease observations, trap counts and image-derived variables. Such models are useful for risk prediction and classification, particularly where structured field data are available.

3.2 Deep Learning and Convolutional Neural Networks

Deep learning uses multilayer neural networks capable of learning hierarchical representations. Convolutional neural networks (CNNs) are especially effective for image analysis because they learn patterns of edges, textures, shapes and spatial arrangements (He *et al*., 2016). Mohanty *et al*. (2016) demonstrated the feasibility of deep learning for image-based plant disease detection, while Ferentinos (2018) evaluated deep-learning models across a large set of plant-disease classes. These studies established a foundation for later crop-specific systems.

3.3 Object Detection and YOLO Models

Object detection differs from ordinary classification because it identifies what is present and where it occurs in the image (Liu & Wang, 2021). YOLO (You Only Look Once) is a widely used family of real-time object-detection models. The original YOLO framework demonstrated the feasibility of unified real-time detection (Redmon *et al*., 2016). Modern versions provide improved detection accuracy and are increasingly used in agricultural applications. For cauliflower, the Cauli-Det study adapted YOLOv8 for disease localisation and classification (Uddin *et al*., 2024).

3.4 Image Segmentation

Segmentation assigns a class label to individual pixels or image regions. In disease management, segmentation can separate healthy leaf tissue from lesions and thereby estimate disease area. A simple severity indicator can be expressed as: Disease severity (%) = diseased area ÷ total assessed area × 100. Pixel-level measurements may provide a more objective estimate than visual scoring, although the reliability of segmentation depends strongly on image quality and accurate annotation.

3.5 Transfer Learning and Efficient Architectures

Transfer learning allows a model pretrained on a large dataset to be adapted to a crop-specific task. It is especially valuable when expert-labelled cauliflower images are limited. EfficientNet is an example of an architecture designed to balance model depth, width and image resolution (Tan & Le, 2019). A recent cauliflower study found EfficientNet-B3 to be the best-performing model among the evaluated architectures, reporting 99.85% accuracy in its experimental dataset (Malik *et al*., 2025). Such results are encouraging but should be interpreted in the context of the particular dataset and validation design.

3.6 Explainable Artificial Intelligence

An AI prediction is more useful to an agronomist when the basis of the prediction can be inspected. Explainable AI methods can highlight image regions that influenced a classification or show important variables in a risk model. For disease diagnosis, visualisation of the lesion or symptom region can help identify obvious model errors. Explainability is therefore important for building confidence among farmers, extension personnel and crop-protection specialists.

4. AI for Cauliflower Disease Management

4.1 Image Acquisition and Preprocessing

The first stage of an AI disease-detection system is image acquisition. Images can be captured using smartphones, digital cameras, fixed cameras, UAVs or specialised sensors. For cauliflower, useful images may include whole plants, individual leaves, curds,

stems and close-up lesions. Metadata such as location, cultivar, crop stage, date, weather and expert diagnosis should be stored with each image.

Preprocessing may include image resizing, noise reduction, normalisation and background handling. Data augmentation—such as controlled rotation, cropping, scaling and illumination changes—can increase training diversity. However, augmentation cannot replace genuine field diversity. A model trained mainly on clean laboratory photographs may fail when deployed in fields containing shadows, soil, weeds, overlapping leaves and variable backgrounds.

4.2 Disease Classification

Classification systems can assign images to healthy, diseased or specific disease categories. The main advantage is rapid screening. A smartphone application could, for example, compare an image with learned disease patterns and return a ranked set of possible classes. Such output should be presented as a decision-support indication rather than definitive laboratory confirmation when symptoms are ambiguous.

High performance on curated datasets is common in published deep-learning research, but performance can decrease substantially under independent field conditions. This is why training, validation and testing should use separate fields and, ideally, separate seasons and locations. Systematic reviews have emphasized dataset quality and generalisation as central issues in plant-disease AI research (Das *et al*., 2024; Pacal *et al*., 2024; Upadhyay *et al*., 2025).

4.3 Disease Localization

Localisation provides an additional level of information by drawing bounding boxes or identifying image regions associated with disease. In the Cauli-Det study, a modified YOLOv8 model was developed for bacterial soft rot, downy mildew and black rot. The reported test performance included 93.2% precision, 82.6% recall and 91.1% mAP (Uddin *et al*., 2024). Localisation can assist users in visually checking the region responsible for a prediction.

4.4 Disease Severity Estimation

Binary disease detection is less informative for management than quantitative severity estimation. If a system can segment lesions and estimate affected tissue, disease progression can be monitored over time. This can support epidemiological experiments, treatment evaluation and crop-protection decisions. A practical research protocol should compare AI-derived severity with independent expert scores to determine agreement and identify systematic errors.

4.5 Disease Forecasting and Early Warning

Disease development is strongly influenced by environmental conditions. AI models can combine historical disease records with temperature, humidity, rainfall, leaf wetness, crop stage and other variables to estimate disease risk. Instead of waiting for severe symptoms, farmers could receive a risk alert prompting intensified scouting. Such models need local calibration because pathogen populations, cultivars, microclimate and production practices differ among regions.

4.6 Differentiating Disease from Abiotic Stress

A major challenge for image-based diagnosis is that nutrient deficiency, water stress, herbicide injury and temperature damage can resemble pathogen symptoms. A robust AI system should therefore include relevant abiotic-stress classes or use a two-stage workflow: first determine whether the symptom is likely biotic or abiotic, and then classify the probable causal category. Expert review remains essential where symptoms overlap.

5. AI for Insect-Pest Management

5.1 Identification of Insect Pests

Automated insect identification can analyse photographs of larvae, adults, eggs or trap catches. CNNs can learn morphological patterns such as body shape, wing structure, colour and segmentation. Transfer learning has been used for crop-insect classification and can reduce the amount of crop-specific training data required (Thenmozhi and Reddy, 2019).

5.2 Automated Counting and Population Estimation

Counting pest individuals is a key component of IPM because management decisions depend on population density. AI object detectors can count visible insects in leaves, traps or field photographs. Repeated automated counts could generate time-series data and reveal population trends earlier than occasional manual scouting. The system should distinguish between individual insects, overlapping individuals and non-target objects.

5.3 Damage Detection

When insects are hidden within foliage or are difficult to photograph, damage-based detection can provide supplementary information. Computer vision may quantify feeding holes, skeletonisation, leaf-area loss or damaged curd tissue. Damage detection

should be interpreted alongside crop stage because the same amount of injury may have different economic consequences at different stages.

5.4 Pest Forecasting

AI forecasting models can combine trap counts, weather variables, crop stage and historical observations. The objective is to estimate the probability of pest population increase or identify periods requiring intensified scouting. A useful system should connect forecasts with action thresholds rather than generate alerts without a management context.

5.5 AI-assisted Biological and Ecological Management

AI can also support ecological IPM. Automated monitoring may help identify pest hotspots while preserving areas with low pest pressure. If natural-enemy observations are incorporated into the dataset, future systems could estimate predator–pest relationships and help avoid unnecessary broad-spectrum interventions. This is consistent with the wider goal of precision agriculture: applying management where and when it is needed.

6. Integration with Integrated Pest Management

The central value of AI lies in its integration with established IPM principles. IPM does not mean simply applying a pesticide whenever a model detects a pest. It involves monitoring, correct identification, prevention, biological and cultural measures, economic thresholds and judicious chemical intervention. AI can strengthen the monitoring and information-management components of this framework.

Table 2. Integration of artificial intelligence-based detection, localization, quantification, forecasting and monitoring with integrated pest management (IPM) decision-making

AI stage	Information generated	IPM decision
Detection	Disease/pest present or absent	Confirm diagnosis
Localization	Where the problem occurs	Prioritize scouting
Quantification	Severity or pest count	Compare with threshold
Forecasting	Risk for coming period	Increase/decrease monitoring
Mapping	Spatial hotspot	Target intervention
Post-treatment analysis	Change in severity/count	Assess effectiveness

A proposed AI-IPM sequence is: image/sensor acquisition → quality control → AI detection → expert verification → severity or pest-density estimation → risk calculation → economic/action threshold → selection of cultural, biological, mechanical or registered chemical measures → post-treatment monitoring. This workflow preserves the role of human expertise while using AI to increase speed and consistency

Precision agriculture and IPM are increasingly considered complementary approaches because spatially targeted information can improve resource-use efficiency and reduce unnecessary crop-protection inputs (Kebe *et al*., 2023). For cauliflower, this could be particularly valuable in intensive vegetable systems where repeated monitoring and high-value produce justify investment in decision-support tools.

7. Smartphone, UAV and Remote-Sensing Applications

7.1 Smartphone-based Diagnosis

Smartphones are attractive because they combine a camera, computing platform and communication device in a single unit. A practical application could guide the user to capture images at an appropriate distance and angle, run a lightweight model and provide a preliminary diagnosis. Smartphone-based plant disease diagnosis has been demonstrated in field-oriented research (Johannes *et al*., 2017; Zhang *et al*., 2024). For cauliflower, a locally trained application could be developed for major regional diseases and pests.

7.2 UAV-based Surveillance

UAVs can acquire repeated aerial images and provide spatial information across fields. AI can analyse these images to identify crop-stress patterns and generate disease or pest hotspot maps. Drone-based plant disease research has increasingly incorporated CNNs and other deep-learning techniques, although dataset availability and field validation remain major limitations (Chin *et al*., 2023).

7.3 Multispectral and Hyperspectral Sensing

RGB images capture visible appearance, whereas multispectral and hyperspectral sensors provide additional spectral information. Disease and nutrient stress can alter plant reflectance before symptoms become obvious to the human eye. Combining spectral signatures with AI may therefore enable earlier stress detection. However, the cost of sensors, calibration requirements and need for large labelled datasets currently limit routine adoption in many smallholder settings.

7.4 Edge AI and Offline Systems

Internet connectivity is not uniformly reliable in agricultural areas. Lightweight AI models that run directly on a smartphone or field device can reduce dependence on cloud connectivity. Model compression, quantization and efficient network architectures are therefore relevant research areas. Offline systems could be particularly useful for extension workers conducting surveys in remote production areas.

8. Advantages of AI-based Disease and Pest Management

Table 3. Comparison of conventional and artificial intelligence-assisted approaches for disease and insect-pest monitoring in cauliflower

Aspect	Conventional monitoring	AI-assisted monitoring
Speed	Periodic/manual	Rapid automated screening
Consistency	Observer dependent	Standardized model output
Disease localization	Usually visual	Automated region detection
Severity estimation	Visual scoring	Potential pixel-based quantification
Pest counting	Labour intensive	Automated counting possible
Large-area assessment	Difficult	UAV/remote sensing possible
Data storage	Manual records	Digital time-series records
Forecasting	Often experience based	Data-driven prediction
Targeting	Field-level	Potential hotspot-level targeting
Learning	Limited from historical records	Models can learn from accumulated datasets

The major practical advantage is not necessarily complete automation but increased monitoring frequency. A farmer or extension worker could use AI to screen many images and focus expert attention on ambiguous or high-risk cases. This human-in-the-loop approach is likely to be more realistic than attempting to remove expert oversight completely.

9. Limitations and Challenges

9.1 Dataset Limitations

AI performance depends heavily on the quality and representativeness of training data. If most images are captured under controlled conditions, the model may learn background or lighting characteristics rather than disease-specific features. A cauliflower dataset should include multiple cultivars, developmental stages, seasons, locations, illumination conditions and symptom severities.

9.2 Class Imbalance and Rare Symptoms

Some diseases or pest stages occur less frequently than others. A model trained on imbalanced data may perform well on common classes while missing rare but important conditions (Lin *et al*., 2017). Balanced sampling, suitable augmentation and class-specific evaluation are required.

9.3 Field Variability

Field conditions are much more complex than laboratory images. Leaves overlap, lesions may be partly hidden, insects move rapidly and backgrounds are variable. Rain droplets and dust can also alter image appearance. Independent field validation is therefore essential.

9.4 Symptom Similarity and False Positives

Disease-like symptoms can arise from nutrient imbalance, chemical injury, temperature stress or mechanical damage. False-positive disease diagnosis could lead to unnecessary treatment, whereas false negatives could delay management. AI systems should therefore report confidence and provide an option for expert confirmation.

9.5 Explainability and Trust

Farmers and agronomists may be reluctant to follow an unexplained AI recommendation. Heat maps, symptom localisation, confidence scores and simple explanations can improve transparency. However, explainability tools themselves should be validated because a visually convincing explanation does not automatically prove that the model is biologically correct.

9.6 Cost and Adoption

Hardware, software development, training, connectivity and maintenance can increase the cost of AI systems. Smallholders may benefit most from low-cost smartphone applications, shared extension platforms or service-based models rather than owning specialised equipment.

9.7 Validation and Standardization

Published accuracy values cannot be compared directly unless datasets, class definitions and evaluation metrics are comparable. Research should report precision, recall, F1-score, sensitivity, specificity, mAP where appropriate, confusion matrices and independent field performance. Multi-location validation should become a routine requirement before recommending a model for operational use.

10. Research Gaps and Future Directions

Several research priorities are apparent. First, there is a need for large, expert-annotated cauliflower datasets containing both disease and pest classes. Second, datasets should include healthy plants and abiotic-stress examples so that models do not force every abnormal appearance into a disease category. Third, multi-season and multi-location data are required to test generalisation.

Fourth, future models should move beyond single-image classification toward multimodal prediction. Image features can be combined with temperature, humidity, rainfall, soil moisture, leaf wetness, crop stage and trap counts. Such integration can improve the biological interpretation of AI predictions. Fifth, disease severity and pest abundance should be connected to economic thresholds so that the system produces management-relevant outputs.

Sixth, research should evaluate the actual agronomic and environmental impact of AI-guided decisions. Useful outcomes include pesticide-use reduction, reduction in crop loss, labour savings, improvement in marketable yield, cost-benefit ratio and effects on beneficial organisms. A model that has 99% image accuracy but does not improve farm decisions may have less practical value than a moderately accurate model that reliably reduces unnecessary interventions.

Seventh, explainable and lightweight models should be developed for field deployment. Eighth, human-in-the-loop systems should be tested with farmers, extension personnel and crop-protection experts. Finally, common annotation protocols and benchmark datasets could improve reproducibility and accelerate comparison of AI approaches.

11. Proposed AI-enabled Cauliflower Protection Framework

Table 4. Artificial intelligence-enabled framework for disease and insect-pest management in cauliflower, showing key stages, activities, outputs and management applications

Stage	Activity	Output	Management use
1. Data acquisition	Smartphone/UAV images; weather; traps	Raw multimodal data	Continuous surveillance
2. Annotation	Expert disease/pest labels	Reference dataset	Reliable model training
3. Preprocessing	Quality control and augmentation	Standardized data	Improved robustness
4. Detection	CNN/YOLO/transformer models	Class + location	Rapid diagnosis
5. Segmentation	Lesion/damage pixel analysis	Affected area	Severity estimate
6. Quantification	Pest count/severity	Numeric indicator	Threshold comparison
7. Forecasting	Weather + history + AI	Risk probability	Early warning
8. Decision layer	IPM rules + thresholds	Recommendation	Targeted management
9. Verification	Expert/farmer confirmation	Validated action	Reduce false decisions
10. Feedback	Post-treatment monitoring	New labelled data	Continuous improvement

The proposed framework is intentionally designed as a decision-support system. The AI model should not independently prescribe a pesticide. Instead, it should provide diagnosis, localisation, severity or abundance information and a risk estimate, which are then interpreted using crop-specific IPM principles and locally approved management recommendations.

12. Conclusion

Artificial intelligence has substantial potential to strengthen disease and pest management in cauliflower. Machine learning can analyse structured crop and environmental information, while deep learning and computer vision can automate disease recognition, localisation, severity estimation and insect-pest detection. Cauliflower-specific studies using modified YOLOv8 and EfficientNet architectures provide encouraging evidence that AI can identify important disease classes under experimental conditions (Uddin *et al*., 2024; Malik *et al*., 2025). Broader research across crops supports the feasibility of CNN-based diagnosis, transfer learning, mobile imaging, real-time object detection and UAV-assisted surveillance (Mohanty *et al*., 2016; Ferentinos, 2018; Fuentes *et al*., 2017; Chin *et al*., 2023).

The most promising future direction is AI-enabled integrated pest management. Detection alone is insufficient; the real value comes when detection is connected with severity, pest density, weather, crop stage, economic thresholds and appropriate management options. AI should therefore complement rather than replace farmers, extension workers, plant pathologists and entomologists. For Indian cauliflower production, especially under variable agro-climatic conditions, locally trained and independently validated models are needed.

Future research should prioritise large field datasets, multi-location validation, multimodal sensing, explainable AI, low-cost edge deployment and rigorous field experiments measuring economic and environmental outcomes. If these challenges are addressed, AI

could contribute to earlier diagnosis, more precise scouting, reduced unnecessary crop-protection inputs, improved resource-use efficiency and more sustainable cauliflower production.

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Declaration of AI Use

This manuscript was prepared through the intellectual contributions of the author(s) to the study design, data analysis, interpretation of results, and scholarly content. Grammarly and ChatGPT were used solely to assist with grammatical refinement and reference formatting during manuscript revision. The author(s) accept full responsibility for the accuracy, integrity, and final content of the manuscript.

Competing Interests

Authors have declared that they have no known competing financial interests or non-financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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