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# The Role of Lightweight Vision Models in Enhancing Precision Pruning and Fruit Thinning Efficiency in Fruit Tree Cultivation

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**ABSTRACT**

The increasing demand for sustainable fruit production and efficient orchard management has accelerated the adoption of artificial intelligence (AI) and precision agriculture technologies in modern farming systems. Traditional pruning and fruit thinning practices in fruit tree cultivation are often labor-intensive, time-consuming, inconsistent, and highly dependent on skilled workers, resulting in rising operational costs and reduced productivity. In response to these challenges, lightweight vision models have emerged as promising smart agricultural technologies capable of supporting real-time image analysis, automated orchard monitoring, and precision pruning and fruit thinning operations. This study examines the role of lightweight vision models in enhancing pruning and fruit thinning efficiency within the context of sustainable fruit tree cultivation. Drawing upon the Diffusion of Innovation (DOI) Theory, Technology Acceptance Model (TAM), and sustainable agriculture perspectives, the study proposes a conceptual framework linking lightweight vision models, operational efficiency, and sustainable orchard management outcomes. The paper argues that lightweight AI-based vision systems can improve pruning accuracy, optimize fruit thinning processes, reduce labor dependency, enhance fruit quality, and increase agricultural productivity through intelligent and data-driven orchard management. In addition, the study highlights the potential contribution of lightweight vision technologies toward precision agriculture, resource optimization, and environmentally sustainable fruit cultivation practices. The findings are expected to provide valuable implications for policymakers, researchers, agricultural engineers, and fruit farmers in promoting smart orchard modernization and sustainable agricultural transformation. However, the applicability of lightweight vision systems should be interpreted as context-dependent, as differences in fruit species, canopy architecture, cultivation systems, environmental conditions, and pruning or thinning requirements may influence model performance and transferability.

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## 1. Introduction

Fruit tree cultivation plays an important role in global agricultural production and food security, contributing significantly to economic development, rural livelihoods, and international fruit supply chains. However, the fruit cultivation industry currently faces numerous challenges, including climate variability, increasing production demands, labor shortages, and the need for sustainable orchard management practices. Traditional orchard operations such as pruning and fruit thinning remain highly labor-intensive and time-consuming, particularly in large-scale fruit farms. These practices are essential for maintaining fruit quality, optimizing canopy structure, improving sunlight penetration, and ensuring stable crop yields. Nevertheless, manual pruning and thinning methods often suffer from inconsistent decision-making, operational inefficiency, and high dependency on skilled labor [35].

One of the most pressing issues in modern orchard management is the increasing shortage of agricultural labor. Many agricultural regions worldwide are experiencing declining numbers of young agricultural workers, aging farming populations, and rising labor costs, which significantly affect orchard productivity and operational sustainability. Recent reports indicate that labor shortages have become a major concern in orchard industries, especially in labor-intensive activities such as pruning, harvesting, and fruit thinning [3]. The growing labor crisis has accelerated the need for agricultural automation technologies capable of reducing human dependency while maintaining operational accuracy and productivity.

In addition, traditional pruning and fruit thinning methods are often inefficient and difficult to scale in modern commercial orchards. Manual operations require substantial labor input and are vulnerable to human error, inconsistent pruning quality, and inefficient resource utilization. Studies have shown that manual pruning alone may account for up to 25 percent of annual labor costs in fruit production systems, particularly in apple orchards and vineyards [35]. Furthermore, conventional orchard management methods frequently struggle to achieve precision in branch selection, fruit density management, and canopy optimization, which may negatively affect fruit quality and overall productivity.

The rising production costs associated with labor, equipment, fertilizers, and orchard maintenance have also increased pressure on fruit farmers to adopt more efficient and sustainable cultivation practices. Increasing operational expenses reduce profitability and threaten the long-term sustainability of fruit farming, particularly for small and medium-scale orchard operators. As a result, precision agriculture and smart farming technologies have emerged as important solutions for improving orchard efficiency, reducing costs, and enhancing agricultural sustainability [21].

Recent advancements in artificial intelligence (AI), machine learning, and computer vision technologies have transformed agricultural management systems by enabling automated monitoring, intelligent decision-making, and real-time crop analysis. AI-driven computer vision systems are increasingly applied in agricultural tasks such as fruit detection, disease monitoring, yield estimation, canopy analysis, and autonomous pruning operations [43,45]. These technologies improve operational precision while supporting data-driven orchard management practices. In particular, computer vision combined with deep learning models has demonstrated substial potential for improving pruning accuracy, fruit thinning decisions, and robotic orchard automation under complex field conditions [3].

Among these technological advancements, lightweight vision models have gained significant attention due to their ability to perform efficient real-time image processing while requiring lower computational resources. Lightweight AI models are particularly suitable for agricultural field deployment because they can operate on edge devices, drones, mobile robots, and embedded systems with limited hardware capacity. Unlike conventional deep learning systems that require high computational power, lightweight vision models offer faster processing speed, lower energy consumption, and greater adaptability for real-time orchard applications [46]. Their integration into precision orchard management systems may significantly enhance pruning efficiency, fruit thinning accuracy, labor optimization, and sustainable fruit cultivation practices.

Consequently, the increasing importance of smart orchard technologies highlights the need for further exploration of lightweight vision models in precision pruning and fruit thinning operations. The integration of AI-driven vision systems into orchard management may contribute toward operational efficiency, agricultural sustainability, and long-term productivity enhancement in fruit tree cultivation systems.

### *1.1 Smart Agriculture and Precision Orchard Management*

The evolution of precision agriculture has significantly transformed modern farming practices from traditional labor-intensive systems into data-driven and technology-oriented agricultural management. Precision agriculture initially focused on the use of geographic information systems (GIS), satellite imagery, and sensor-based technologies to improve field-level management and optimize agricultural inputs. Over time, advancements in digital technologies, artificial intelligence (AI), Internet of Things (IoT), robotics, and machine vision systems have accelerated the development of smart agriculture, enabling more precise and efficient farming operations [14,32]. Precision agriculture aims to improve productivity, reduce resource wastage, minimize environmental impacts, and enhance agricultural sustainability through real-time monitoring and intelligent decision-making systems.

Within the agricultural sector, orchard management has increasingly adopted smart farming technologies to improve fruit production efficiency and crop quality. Smart orchard technologies integrate sensors, drones, AI-based image processing systems, robotics, and automated monitoring platforms to support precision fruit cultivation and orchard management. These technologies allow farmers to monitor tree growth, fruit maturity, disease occurrence, canopy structure, and environmental conditions more accurately and efficiently. Recent studies have shown that AI-enhanced orchard systems improve operational efficiency while supporting sustainable fruit production and reducing labor dependency [18]. Lightweight computer vision systems and AI-based monitoring technologies are particularly important for orchard environments due to their ability to perform real-time detection and analysis under complex field conditions while minimizing computational costs.

Artificial intelligence has become one of the most transformative technologies in fruit cultivation and precision orchard management. AI technologies such as machine learning, deep learning, computer vision, and neural networks are increasingly utilized for fruit detection, yield estimation, disease monitoring, crop-load management, automated harvesting, pruning, and fruit thinning operations. Machine vision systems using convolutional neural networks (CNNs) and object detection algorithms such as YOLO have demonstrated high accuracy in identifying flowers, fruits, branches, and canopy structures in orchard environments [2,25]. These AI-driven systems enable real-time orchard monitoring and automated decision-making, which improve operational efficiency and reduce human error in fruit cultivation processes. Furthermore, AI applications in fruit farming contribute to higher productivity, improved fruit quality, and more sustainable orchard management practices [23,49].

The digital transformation of agricultural management has further strengthened the adoption of intelligent farming systems across the agricultural industry. Modern agricultural management increasingly relies on digital platforms, cloud computing, IoT-based monitoring systems, remote sensing technologies, and AI-powered analytics to support data-driven farming decisions. These technologies enable farmers to collect and analyze real-time agricultural data related to soil conditions, weather patterns, irrigation requirements, crop health, and orchard productivity. The integration of digital technologies into agricultural operations enhances resource optimization, operational efficiency, and sustainability while improving farmers' ability to respond to environmental and market challenges [13,14]. Digital agriculture also supports predictive analytics and automated farm management, allowing agricultural practitioners to improve long-term planning and productivity management.

Automation and intelligent farming systems are increasingly becoming essential components of sustainable agricultural modernization. Automated agricultural technologies such as robotic pruning systems, autonomous harvesting machines, intelligent irrigation systems, and AI-powered monitoring devices reduce labor dependency and improve precision in agricultural operations. In fruit tree cultivation, automation technologies are especially important due to increasing labor shortages and the complexity of orchard management tasks such as pruning, thinning, and harvesting. Lightweight vision models and intelligent automation systems enable real-time object detection and operational guidance while maintaining low computational requirements suitable for field deployment [1]. These intelligent farming systems support the transition toward sustainable, scalable, and efficient orchard management practices while contributing to environmental conservation and agricultural competitiveness.

### *1.2 Lightweight Vision Models in Agriculture*

Lightweight vision models refer to compact artificial intelligence (AI) and computer vision architectures designed to perform image recognition, object detection, and visual analysis tasks with lower computational complexity, reduced memory consumption, and faster processing speed compared to conventional deep learning models. These models are specifically optimized for deployment in resource-constrained environments such as mobile devices, drones, embedded sensors, and edge computing systems commonly used in agricultural fields. Lightweight models, including MobileNet, ShuffleNet, EfficientNet, and YOLO-based compact architectures, have become increasingly important in smart agriculture because they allow real-time image processing while maintaining acceptable accuracy and operational efficiency [8,24].

Recent advancements in real-time image processing technologies have significantly transformed precision agriculture and orchard management systems. Real-time image processing enables agricultural systems to instantly capture, analyze, and interpret visual data from crops, fruits, leaves, branches, and surrounding environments for rapid decision-making. Through the integration of cameras, sensors, drones, and edge AI systems, agricultural operations such as fruit detection, pruning, disease identification, and fruit thinning can be automated more efficiently. Ghazal [14] explained that computer vision technologies now support the entire digital lifecycle of crop management, including image acquisition, image analysis, planning, monitoring, and automated treatment processes in precision farming. Furthermore, advances in deep learning-assisted image processing technologies have improved the speed, precision, and scalability of agricultural monitoring systems, particularly under dynamic field conditions [5].

Deep learning and computer vision systems have emerged as core technological foundations in modern smart agriculture. Deep learning enables AI systems to automatically learn visual features from large agricultural image datasets without requiring manual feature extraction. Computer vision systems integrated with convolutional neural networks (CNNs), vision transformers, and object detection algorithms can accurately recognize fruits, branches, leaves, pests, and diseases under varying environmental conditions. According to Upadhyay *et al*., [41], deep learning-based computer vision systems provide non-destructive, fast, precise, and real-time agricultural monitoring capabilities, making them highly suitable for precision agriculture applications. In orchard management, these technologies are increasingly applied for automated pruning, fruit counting, yield estimation, and fruit thinning operations to improve operational efficiency and agricultural productivity.

One of the major advantages of lightweight AI models in agriculture is their ability to operate efficiently on low-power and resource-constrained hardware platforms. Traditional deep learning models often require high-performance computing resources, large storage capacity, and expensive graphical processing units (GPUs), limiting their applicability in rural farming environments. Lightweight AI models overcome these limitations by reducing model size and computational requirements while maintaining high predictive accuracy. Research by Joshi [24] demonstrated that lightweight YOLO-based architectures can achieve high detection performance with minimal computational overhead, making them highly suitable for edge deployment in agricultural environments. Similarly, Shafik et al. (2025) found that lightweight deep learning models significantly reduce memory usage and inference time while supporting accurate agricultural disease classification in low-resource environments. These advantages enhance the feasibility of deploying AI systems directly in orchards and farming fields.

Resource-efficient AI systems also play a critical role in enabling field deployment and practical adoption of precision agriculture technologies. Agricultural environments often face limitations related to internet connectivity, power supply, hardware availability, and environmental variability. Lightweight vision models support edge computing capabilities by processing data locally without relying heavily on cloud infrastructure, thereby reducing latency and improving operational responsiveness. Resource-efficient systems additionally lower implementation costs and energy consumption, making smart farming technologies more accessible to small-scale and medium-scale farmers. Cao *et al*., [8] emphasized that resource-efficient AI and computer vision technologies are essential for transitioning agriculture from labor-intensive practices toward intelligent and sustainable farming systems. Therefore, lightweight vision models represent a promising technological advancement capable of enhancing precision pruning, fruit thinning efficiency, and sustainable orchard management in modern agriculture.

### *1.3 Precision Pruning and Fruit Thinning Efficiency*

Precision pruning refers to the application of intelligent and data-driven techniques in selectively removing branches, shoots, or plant structures to optimize fruit tree growth, canopy structure, sunlight interception, and crop productivity. In modern orchard management, precision pruning has evolved from conventional manual practices toward technology-assisted systems involving artificial intelligence (AI), machine vision, robotics, and computer vision analytics. These technologies enable accurate identification of pruning points and improve consistency in orchard operations. Recent studies highlighted that precision pruning guided by computer vision and robotic systems significantly improves operational accuracy, reduces labor dependency, and enhances orchard management efficiency [3,51]. Furthermore, intelligent pruning systems contribute toward more sustainable fruit production by optimizing canopy management and reducing unnecessary vegetative growth, thereby improving overall orchard productivity and resource utilization.

Fruit thinning is another essential orchard management practice that involves removing excess flowers or young fruits to regulate crop load and improve fruit quality. Proper fruit thinning allows fruit trees to allocate nutrients and energy more efficiently, resulting in larger fruit size, better coloration, improved sugar accumulation, and enhanced market quality. According to recent research, precision crop load management and intelligent fruit thinning technologies contribute significantly toward maximizing fruit quality, uniformity, and economic value in orchard production systems [39,47]. In addition, machine vision systems integrated with lightweight deep learning models enable more accurate fruit detection and crop load estimation, which are critical for effective thinning operations in complex orchard environments [37,50].

The integration of lightweight vision models into precision pruning and fruit thinning operations also contributes substantially to labor efficiency and operational optimization. Traditional orchard management practices are highly labor-intensive, time-consuming, and increasingly challenged by labor shortages and rising labor costs. Smart vision-based systems provide automated or semi-automated solutions capable of real-time monitoring, target recognition, and precision decision-making. Studies have shown that lightweight AI models and machine vision technologies improve operational speed, reduce manual intervention, and enhance the scalability of orchard management systems [37,50]. These systems are particularly valuable in large-scale orchards where efficient labor management and operational consistency are essential for maintaining productivity and profitability.

Moreover, precision pruning and fruit thinning directly contribute toward yield quality improvement. By optimizing crop load and tree structure, these practices improve light penetration, air circulation, nutrient allocation, and fruit development. Previous studies reported that precision orchard management technologies improve fruit size uniformity, reduce physiological disorders, and enhance harvesting efficiency [39]. Lightweight vision models also facilitate accurate fruit localization, growth monitoring, and maturity detection, which support better harvesting and orchard planning decisions [18]. Consequently, precision orchard technologies play an important role in improving fruit quality standards and increasing the market competitiveness of fruit producers.

Precision pruning and fruit-thinning technologies may also contribute indirectly to more efficient resource management in orchard systems. However, reductions in fertilizer or pesticide use should not be attributed to lightweight vision models alone. Such reductions are more directly associated with applications in which machine vision, artificial intelligence, or sensing technologies are integrated with site-specific or variable-rate application systems. In these applications, visual information about tree canopies, crop conditions, or treatment targets can be translated into more targeted agricultural interventions, thereby reducing unnecessary application outside the required treatment areas. Consequently, the sustainability contribution of lightweight vision technologies should be understood as application-specific and dependent on their integration with appropriate precision-management technologies rather than as an inherent outcome of AI adoption.

### *1.4 Fruit Tree Cultivation and Agricultural Sustainability*

Fruit tree cultivation plays a critical role in global food production, rural economic development, and environmental sustainability. However, modern orchard systems face increasing challenges related to climate change, labor shortages, excessive chemical input usage, resource depletion, and declining productivity efficiency. These challenges have accelerated the transition toward sustainable orchard management practices that integrate precision agriculture, smart farming technologies, and environmentally responsible cultivation systems. Sustainable orchard management emphasizes efficient resource utilization, ecological balance, and long-term productivity while minimizing environmental degradation and operational inefficiencies [29]. Precision horticulture technologies such as artificial intelligence (AI), Internet of Things (IoT), machine vision systems, and automated monitoring tools are increasingly adopted to improve orchard sustainability, optimize fruit production, and reduce excessive agricultural inputs.

One of the primary objectives of sustainable fruit tree cultivation is enhancing productivity and fruit quality while maintaining environmental efficiency. Precision orchard management enables farmers to monitor canopy conditions, soil moisture, nutrient levels, pest infestations, and crop growth in real time, allowing more accurate and timely agricultural interventions. Recent studies indicate that smart orchard technologies improve fruit quality, optimize crop load management, and enhance harvesting decisions through advanced sensing and image-processing systems [46]. Furthermore, precision pruning and fruit thinning technologies contribute significantly to improving fruit size, color, maturity uniformity, and overall yield quality by optimizing resource allocation within the tree canopy [25]. These technologies support more consistent orchard performance while reducing unnecessary wastage of water, fertilizers, and labor resources.

In addition to productivity enhancement, sustainable fruit cultivation also focuses on reducing production costs and improving operational efficiency in orchard management. Traditional orchard operations such as pruning, thinning, monitoring, and harvesting are highly labor-intensive and increasingly costly due to labor shortages and rising wages. Smart farming technologies and lightweight vision models provide automated and semi-automated solutions that reduce dependency on manual labor while improving operational precision and efficiency. Research has shown that AI-driven orchard systems and precision agriculture technologies significantly reduce operational costs through optimized resource management, targeted interventions, and data-driven decision-making processes. Moreover, automated monitoring systems improve fertilizer and irrigation efficiency, reducing excessive input usage and improving profitability among fruit farmers.

Long-term agricultural sustainability is another important consideration in modern fruit tree cultivation. Sustainable orchard systems aim to maintain soil fertility, biodiversity, water conservation, and ecosystem stability while ensuring long-term economic viability for farmers. Excessive chemical fertilizer application, pesticide overuse, and inefficient irrigation practices can negatively affect soil health, environmental quality, and orchard productivity over time. Therefore, integrating precision agriculture technologies into orchard management supports sustainable intensification by improving nutrient management, reducing environmental pollution, and enhancing ecological efficiency. Smart farming systems also contribute to climate-resilient agriculture by enabling more adaptive and responsive management practices based on real-time environmental conditions and predictive analytics.

Furthermore, smart farming technologies significantly improve environmental efficiency in orchard systems through precise resource application and continuous environmental monitoring. Precision agriculture technologies allow farmers to apply fertilizers, pesticides, and irrigation inputs only where and when needed, minimizing waste and reducing environmental impacts. AI-powered vision systems, sensors, drones, and robotic technologies also improve orchard monitoring capabilities, contributing to more sustainable and environmentally responsible farming operations [23]. The integration of lightweight vision models and intelligent orchard management systems therefore represents an important advancement toward achieving sustainable fruit production systems that balance economic profitability, environmental conservation, and agricultural productivity.

### *1.5 Theoretical Foundation*

This study draws upon the Diffusion of Innovation (DOI) Theory and the Technology Acceptance Model (TAM) as complementary theoretical lenses for explaining the adoption and effective utilisation of lightweight vision technologies in precision orchard management. The integration of these perspectives is appropriate because the adoption of lightweight agricultural technologies involves both the characteristics of the technological innovation itself and users' evaluations of whether the technology is useful and sufficiently easy to employ in agricultural operations. Rather than treating DOI and TAM as competing explanations, this study conceptualises them as addressing different but related stages of technology adoption and utilisation.

The Diffusion of Innovation Theory developed by Rogers explains how characteristics of an innovation influence its adoption and diffusion. Five attributes are particularly relevant: relative advantage, compatibility, complexity, trialability, and observability. Within the context of lightweight vision models, relative advantage refers to the extent to which these technologies offer improvements over conventional orchard-management practices, such as faster image processing, reduced computational requirements, improved detection capability, and greater potential for automation. Compatibility concerns whether lightweight vision technologies can be integrated with existing orchard practices, robotic systems, edge devices, and farm-management processes. Complexity reflects the technological and operational difficulty associated with implementing and operating the systems, while trialability and observability concern the ability of users to experiment with the technology and observe its operational benefits before wider implementation. These innovation characteristics therefore provide a technological-level explanation of why lightweight vision systems may be considered suitable for adoption in precision orchard environments.

TAM complements DOI by explaining how potential users cognitively evaluate a technology. Davis (1989) identified perceived usefulness and perceived ease of use as central determinants of technology acceptance. In the present context, perceived usefulness reflects the extent to which orchard managers and agricultural practitioners believe that lightweight vision systems can improve pruning accuracy, fruit-thinning efficiency, operational speed, labour productivity, and orchard-management performance. Perceived ease of use concerns the degree to which these technologies can be operated, deployed, and integrated into existing agricultural practices without excessive technological difficulty. The relatively lower computational requirements and potential deployment of lightweight models on edge devices, mobile systems, and agricultural robots may strengthen perceptions of ease of use, although actual usability remains dependent on system design, technical expertise, infrastructure, and field conditions.

The integration of DOI and TAM therefore provides a more complete explanation of lightweight vision technology adoption than either perspective alone. DOI primarily explains how the characteristics of the innovation influence its attractiveness and suitability for adoption, whereas TAM explains how users translate these characteristics into perceptions of usefulness and ease of use. For example, the relative advantage of faster detection or greater operational precision may strengthen perceived usefulness, while lower technological complexity may enhance perceived ease of use. Compatibility with existing orchard practices may similarly influence both perceptions. Previous precision-agriculture research has demonstrated the value of combining technology-acceptance and diffusion-of-innovation perspectives when explaining farmers' adoption of agricultural information technologies.

Within the conceptual framework proposed in this study, DOI and TAM do not constitute additional empirical variables. Instead, they provide the theoretical rationale explaining why lightweight vision models may be accepted and effectively utilised within precision orchard-management systems. Once adopted and effectively utilised, the technological capabilities of lightweight vision models—such as real-time detection, computational efficiency, image-processing capability, and field adaptability—are proposed to enhance precision pruning and fruit-thinning efficiency. Improved operational efficiency may subsequently contribute to sustainable fruit-tree cultivation through improved productivity, resource optimisation, labour efficiency, fruit-quality management, and more efficient orchard operations.

Accordingly, the theoretical mechanism proposed in this study can be expressed as follows:

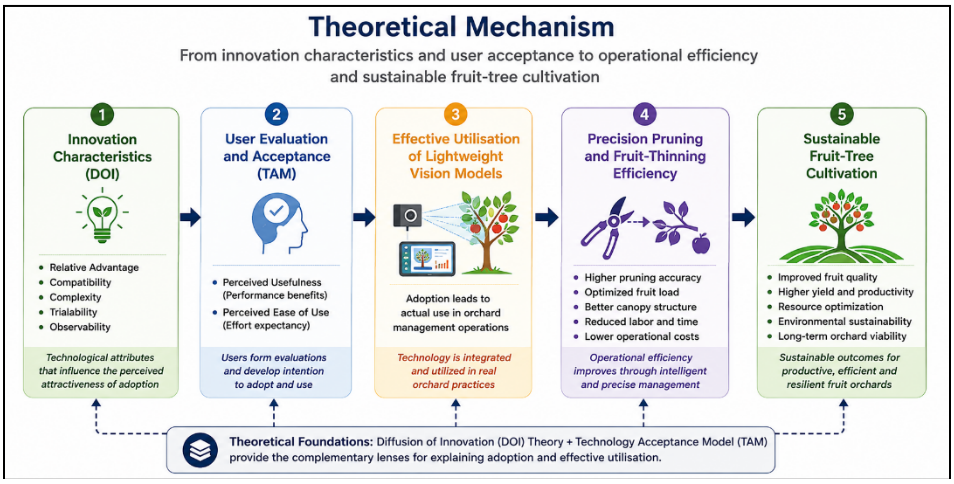


**Fig. 1.** Theoretical mechanism

This theoretical integration extends the discussion beyond the question of whether agricultural practitioners adopt a technology toward explaining how adoption and effective utilisation may translate technological capability into operational and sustainability outcomes. As the present study is conceptual, these relationships represent theoretically derived propositions rather than empirically established causal relationships and require subsequent empirical validation.

### *1.6 Research Gap, Significance, and Objectives*

The rapid advancement of artificial intelligence (AI), computer vision, and deep learning technologies has significantly transformed modern agricultural practices, particularly in the area of precision agriculture and smart orchard management. Lightweight vision models have emerged as promising technologies due to their ability to perform real-time image recognition, object detection, and intelligent decision-making while operating with lower computational requirements and energy consumption. These technologies are increasingly being applied in fruit tree cultivation for tasks such as fruit detection, pruning assessment, canopy monitoring, and fruit thinning operations. However, despite the growing interest in AI-driven agricultural systems, the current literature remains fragmented and underdeveloped regarding the practical and sustainability implications of lightweight vision models in orchard management.

Existing studies on lightweight vision models primarily focus on technical performance indicators such as detection accuracy, algorithm optimization, image classification precision, and computational speed [10,46]. While these technical advancements are important, limited attention has been given to operational efficiency outcomes such as labor reduction, pruning effectiveness, resource optimization, and overall orchard management efficiency. Most studies emphasize machine learning architecture performance without sufficiently addressing how these technologies contribute to improving agricultural productivity and operational sustainability in real farming environments. Consequently, there remains a significant gap between technological innovation and practical agricultural implementation.

Furthermore, the integration between AI-based vision systems and sustainable agricultural outcomes remains insufficiently explored. Sustainable fruit cultivation requires not only technological accuracy but also environmentally responsible and economically efficient farming practices. Recent studies suggest that precision agriculture technologies have substantial potential to reduce resource wastage, optimize agricultural inputs, and improve sustainability performance; however, empirical and conceptual discussions linking lightweight vision systems with sustainability outcomes in orchard management are still limited. Existing agricultural AI studies often overlook broader sustainability dimensions such as long-term productivity, environmental efficiency, operational cost reduction, and sustainable orchard management practices.

Another important gap concerns the limited research linking precision orchard technologies with productivity enhancement and cost efficiency. Although several studies acknowledge the role of AI technologies in improving agricultural automation, insufficient research explains how lightweight vision models directly contribute to pruning and fruit thinning efficiency and subsequently influence fruit quality, yield optimization, and production cost management [50]. The economic implications of AI-assisted orchard management technologies remain underexplored, particularly in relation to sustainable agricultural competitiveness and farmers' operational performance.

Although DOI and TAM have previously been applied individually and jointly to explain the adoption of agricultural and precision-farming technologies, considerably less attention has been directed toward using these complementary perspectives to explain how the adoption and effective utilisation of lightweight vision technologies may translate into operational and sustainability outcomes in precision orchard management. Existing research has predominantly concentrated either on technology-adoption behaviour or on the technical performance of computer vision architectures. Consequently, a conceptual gap remains in connecting innovation characteristics and user acceptance with the operational mechanisms through which lightweight vision systems may improve precision pruning and fruit-thinning efficiency and subsequently contribute to sustainable fruit-tree cultivation. This study addresses this gap by using DOI and TAM as complementary theoretical lenses while positioning pruning and thinning efficiency as the operational mechanism connecting technological utilisation with sustainable cultivation outcomes.

Therefore, this study addresses these gaps by proposing a conceptual framework examining the role of lightweight vision models in enhancing precision pruning and fruit thinning efficiency and their contribution toward sustainable fruit tree cultivation. The study argues that operational efficiency serves as an important mechanism through which lightweight vision technologies improve agricultural sustainability and productivity. The rationale of this study lies in the increasing need for smart, sustainable, and resource-efficient orchard management systems capable of addressing labor shortages, rising production costs, and environmental sustainability challenges in modern fruit cultivation.

This study aims to examine the role of lightweight vision models in enhancing precision pruning and fruit thinning efficiency within the context of smart orchard management and sustainable fruit tree cultivation. Specifically, the study seeks to investigate the relationship between pruning and thinning efficiency and sustainable fruit cultivation outcomes, including productivity improvement, resource optimization, and operational sustainability. In addition, the study aims to examine the mediating role of precision pruning and fruit thinning efficiency in the relationship between lightweight vision models and sustainable fruit tree cultivation. Through this investigation, the study intends to provide a comprehensive theoretical understanding of how AI-driven vision technologies contribute to operational efficiency and long-term sustainability in modern orchard management systems.

This study provides several important theoretical, practical, and agricultural contributions to the growing literature on precision agriculture, artificial intelligence, and sustainable orchard management. From a theoretical perspective, the study contributes to the advancement of smart agriculture literature by integrating lightweight vision models, operational efficiency, and sustainable fruit cultivation within a unified conceptual framework. The study also extends the application of the Diffusion of Innovation (DOI) Theory and Technology Acceptance Model (TAM) in explaining the adoption and effectiveness of AI-driven agricultural technologies in orchard management contexts.

From a practical perspective, the study offers valuable insights for agricultural practitioners, orchard managers, technology developers, and policymakers regarding the implementation of lightweight AI vision systems in fruit tree cultivation. The proposed framework may assist stakeholders in understanding how precision pruning and fruit thinning technologies can improve labor efficiency, reduce operational costs, optimize fruit quality, and enhance orchard productivity. The study also supports the development of smart farming strategies capable of addressing labor shortages and increasing agricultural competitiveness.

In terms of sustainability, the study contributes toward promoting environmentally responsible and resource-efficient farming systems. The integration of lightweight vision models in orchard management may help reduce unnecessary resource consumption, improve precision agricultural practices, and support sustainable fruit production systems. Consequently, the study provides important implications for agricultural modernization and the long-term sustainability of smart orchard management practices.

## 2. Methodology

This study adopts a conceptual research design to examine the role of lightweight vision models in enhancing precision pruning and fruit thinning efficiency within sustainable fruit tree cultivation. Rather than collecting and analysing primary empirical data, the study synthesises existing literature on lightweight artificial intelligence, computer vision, precision agriculture, orchard automation, pruning and fruit thinning, and sustainable fruit cultivation to develop an integrated conceptual explanation of the relationships among these areas.

The conceptual development is informed by the Diffusion of Innovation (DOI) Theory, Technology Acceptance Model (TAM), and sustainable agriculture perspectives. These theoretical perspectives are used to explain how the technological characteristics and potential acceptance of lightweight vision systems may facilitate their utilisation in orchard management and how such utilisation may contribute to operational improvements in precision pruning and fruit thinning.

Based on the synthesis of theoretical and empirical literature, the study proposes a conceptual framework linking lightweight vision models, precision pruning and fruit thinning efficiency, and sustainable fruit tree cultivation. Lightweight vision models are conceptualised as the technological component, while precision pruning and fruit thinning efficiency represents the operational mechanism through which these technologies may contribute to sustainable cultivation outcomes. The proposed relationships are presented as theoretically derived propositions requiring subsequent empirical validation rather than as empirically established causal relationships.

### *2.2 Model Development*

The rapid advancement of artificial intelligence (AI), deep learning, and computer vision technologies has significantly transformed modern agricultural practices, particularly within precision agriculture and smart orchard management systems. In fruit tree cultivation, lightweight vision models have emerged as an important technological innovation capable of supporting real-time orchard monitoring, precision pruning, and automated fruit thinning processes. Lightweight vision models refer to computationally efficient deep learning and computer vision systems designed for deployment in resource-constrained agricultural environments, including edge devices, drones, robotic systems, and mobile smart farming platforms. Compared with traditional heavy AI architectures, lightweight models provide faster image processing, lower computational requirements, reduced energy consumption, and improved real-time operational capability in field conditions [1,50]. These technologies are increasingly recognized as critical components of smart agriculture because they enable precision-based decision-making and reduce reliance on manual labor in orchard management.

The relationship between lightweight vision models and precision pruning and fruit thinning efficiency can be explained through the capability of AI-driven systems to improve operational accuracy, speed, and consistency in orchard management. Precision pruning and fruit thinning are essential agricultural practices that directly influence fruit quality, yield optimization, crop load balance, and overall orchard productivity. Traditional pruning and thinning methods are often labor-intensive, time-consuming, and dependent on human judgment, which may lead to inconsistencies and operational inefficiencies. Recent studies have shown that machine vision systems and lightweight deep learning models can significantly improve the identification of buds, flowers, branches, and fruits in complex orchard environments, thereby enhancing pruning precision and thinning accuracy [25,37]. Furthermore, lightweight AI models facilitate real-time deployment in orchards by enabling rapid object detection and decision-making with minimal computational overhead, making them suitable for autonomous robotic pruning and smart orchard systems [35,47].

The relationship between pruning and fruit thinning efficiency and sustainable fruit tree cultivation is also highly significant within the context of precision agriculture. Efficient pruning and thinning operations contribute to improved fruit quality, balanced crop load distribution, optimized nutrient allocation, and enhanced orchard productivity. In addition, precision orchard management reduces excessive resource utilization, minimizes operational costs, and supports environmentally sustainable agricultural practices. Previous research indicates that computer vision technologies and intelligent orchard management systems improve agricultural sustainability by reducing labor dependency, enhancing resource optimization, and supporting data-driven crop management decisions [14,49]. Efficient pruning and thinning also contribute to healthier canopy structures, better sunlight penetration, disease reduction, and improved long-term orchard sustainability [39]. Consequently, precision orchard efficiency becomes an important mechanism through which smart agricultural technologies support sustainable fruit cultivation systems.

The proposed mediation mechanism is conceptually consistent with the complementary roles of DOI and TAM, although neither theory directly predicts sustainable agricultural outcomes. DOI provides a basis for understanding how the characteristics of lightweight vision technologies may influence their adoption, while TAM explains how potential users evaluate their usefulness and ease of use. Adoption and acceptance alone, however, do not automatically produce sustainable outcomes. The present study therefore extends the theoretical logic by proposing that value is generated through the effective utilisation of lightweight vision systems in specific orchard operations. Precision pruning and fruit-thinning efficiency consequently represent the operational mechanism through which accepted and utilised technologies may contribute to sustainable fruit-tree cultivation.

### *2.3 Hypothesis Development*

The advancement of lightweight vision models has significantly transformed precision agriculture and smart orchard management by enabling real-time image recognition, automated decision-making, and efficient operational control in fruit cultivation systems. Lightweight vision models refer to resource-efficient artificial intelligence (AI) and computer vision systems capable of operating effectively under constrained computational environments while maintaining high detection accuracy. In orchard management, these technologies are increasingly utilized for precision pruning, fruit thinning, crop-load estimation, and fruit detection due to their ability to perform rapid image processing and intelligent object recognition in complex orchard environments. Recent studies have emphasized that lightweight deep learning and computer vision models improve operational efficiency by reducing manual labor dependency and increasing pruning and thinning accuracy in orchard systems [37,50].

Furthermore, lightweight AI models facilitate precision orchard management through real-time monitoring and automated crop-load optimization. Vision-guided intelligent systems have been found to improve pruning precision, reduce operational errors, and enhance fruit thinning decisions through automated image segmentation and branch detection technologies [14,39]. In addition, recent advancements in lightweight fruit detection networks and machine vision systems have demonstrated strong capabilities in handling dense orchard environments, occlusions, and variable lighting conditions while maintaining computational efficiency suitable for field deployment [37,50]. Therefore, lightweight vision models are expected to significantly improve precision pruning and fruit thinning efficiency in fruit tree cultivation.

H1: Lightweight vision models significantly enhance precision pruning and fruit thinning efficiency.

Precision pruning and fruit thinning are important orchard management practices that directly influence fruit quality, crop productivity, and long-term orchard sustainability. Efficient pruning and thinning operations help optimize tree architecture, improve sunlight penetration, enhance air circulation, and regulate crop load, thereby contributing to healthier fruit development and higher-quality yields. Traditional manual pruning and thinning methods are often labor-intensive, time-consuming, and inconsistent, which may reduce operational efficiency and increase production costs. Recent studies indicate that precision orchard management technologies improve agricultural sustainability through optimized crop-load management, reduced resource wastage, and enhanced fruit quality [47].

Additionally, efficient pruning and thinning operations contribute to sustainable fruit cultivation by improving resource utilization and reducing excessive input dependency. Smart orchard systems supported by machine vision technologies enable more accurate pruning and thinning decisions, which enhance productivity while minimizing unnecessary labor and operational costs [2,25]. Sustainable orchard management also benefits from improved fruit uniformity, better yield estimation, and enhanced crop health monitoring enabled by AI-driven agricultural technologies [23,32]. Consequently, precision pruning and fruit thinning efficiency are expected to significantly improve sustainable fruit tree cultivation.

H2: Precision pruning and fruit thinning efficiency significantly improve sustainable fruit tree cultivation.

The relationship between lightweight vision models and sustainable fruit tree cultivation may be better explained through the mediating role of precision pruning and fruit thinning efficiency. While lightweight vision technologies provide intelligent monitoring, detection, and decision-support capabilities, the actual contribution of these technologies toward sustainable orchard management occurs through improvements in operational efficiency. In other words, AI-based vision systems enhance sustainability outcomes by enabling more accurate pruning and thinning practices, optimizing crop-load management, reducing labor intensity, and improving resource allocation in orchard environments. Previous studies have highlighted that machine vision systems and AI-guided orchard management technologies improve sustainability performance through operational optimization and precision agricultural interventions [14,37].

Moreover, precision operational efficiency serves as an important mechanism translating technological innovation into practical agricultural sustainability outcomes. Lightweight vision models alone may not directly guarantee sustainable fruit cultivation unless they successfully improve pruning accuracy, fruit thinning performance, and orchard management efficiency. Studies on AI-enhanced precision orchard management reported that intelligent vision systems contribute to improved yield quality, reduced production costs, and enhanced environmental sustainability primarily through optimized operational processes [47,49]. Therefore, precision pruning and fruit thinning efficiency are proposed to mediate the relationship between lightweight vision models and sustainable fruit tree cultivation.

H3: Precision pruning and fruit thinning efficiency mediate the relationship between lightweight vision models and sustainable fruit tree cultivation.

*2.6 Conceptual Framework*

Figure 1 illustrates the proposed conceptual framework examining the role of lightweight vision models in enhancing sustainable fruit tree cultivation through precision pruning and fruit thinning efficiency. The framework identifies lightweight vision models as the independent variable, consisting of dimensions such as real-time detection capability, image processing efficiency, AI model accuracy, computational efficiency, and field adaptability. These technological capabilities are expected to improve operational processes in orchard management by enabling accurate and efficient pruning and fruit thinning activities. Precision pruning and fruit thinning efficiency serve as the mediating variable, encompassing operational accuracy, labor reduction, time efficiency, resource optimization, and fruit quality improvement. The framework proposes that improvements in these operational efficiencies contribute directly to sustainable fruit tree cultivation, which is reflected through productivity enhancement, cost efficiency, fruit quality sustainability, environmental sustainability, and orchard management performance. Overall, the framework suggests that lightweight vision models enhance sustainable fruit cultivation indirectly through their positive influence on pruning and fruit thinning efficiency within smart orchard management systems.

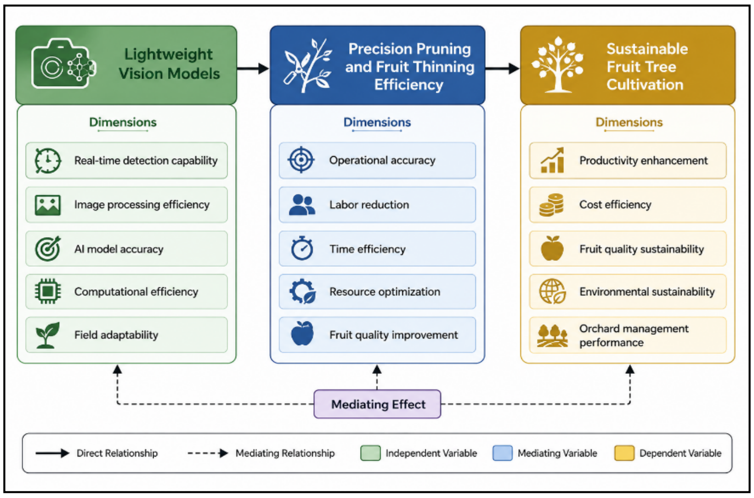


**Fig. 2**. Conceptual framework

## 3. Discussion

### *3.1 Lightweight Vision Models and Precision Orchard Efficiency*

The integration of lightweight vision models into orchard management has significantly transformed precision agriculture by enabling faster, more efficient, and data-driven cultivation practices. Lightweight artificial intelligence (AI) and computer vision technologies are increasingly utilized in fruit tree cultivation due to their ability to perform real-time image processing while maintaining low computational complexity and energy consumption. These systems are particularly important in orchard environments where real-time monitoring, mobile deployment, and edge-device compatibility are essential for operational efficiency. Recent studies emphasized that lightweight deep learning and computer vision models improve the adaptability of precision agricultural systems in complex field environments while reducing deployment costs and computational burdens [50].

One of the major applications of lightweight vision models in orchard management is AI-based pruning optimization. Traditional pruning practices depend heavily on manual labor and human expertise, resulting in inconsistent pruning quality, high operational costs, and labor shortages during peak agricultural seasons. AI-powered vision systems can identify branches, canopy structures, and pruning points with high precision through image recognition and deep learning algorithms. Studies have shown that machine vision and robotic pruning systems improve pruning accuracy, reduce unnecessary branch removal, and optimize canopy management for better light distribution and fruit productivity [51]. Furthermore, lightweight AI models enable faster processing speeds and field deployment through mobile devices, drones, and autonomous orchard robots, making precision pruning more practical and scalable for modern orchards.

Real-time orchard monitoring also represents an important advancement facilitated by lightweight vision models. Through integrated cameras, sensors, drones, and IoT systems, orchard conditions can be continuously monitored to detect fruit growth, canopy density, branch conditions, and environmental changes. Recent research highlighted that computer vision systems provide accurate and real-time crop analytics that support decision-making processes in precision farming and smart orchard management [14]. Real-time monitoring allows orchard managers to respond quickly to changes in crop conditions, improving operational efficiency and reducing losses caused by delayed interventions.

Another important contribution of lightweight vision systems is the reduction of dependency on manual labor. Labor shortages and rising labor costs have become critical challenges in fruit tree cultivation, particularly for labor-intensive activities such as pruning and fruit thinning. Intelligent vision systems automate repetitive orchard tasks by utilizing object detection, image segmentation, and robotic guidance technologies. Research by Pawikhum *et al.*, [37] demonstrated that machine vision systems for apple bud thinning significantly reduced manual workload while maintaining accurate detection and counting performance in complex orchard environments. Recent lightweight fruit-detection models have demonstrated promising performance under challenging orchard conditions, including dense targets, partial occlusion, and variable environmental conditions. However, such performance is generally dependent on the characteristics of the training dataset, model architecture, imaging conditions, and evaluation environment. Robustness under one experimental setting should therefore not be interpreted as evidence of equivalent performance across different orchards, fruit species, seasons, or deployment conditions.

Intelligent fruit thinning systems also play a significant role in improving fruit quality and yield consistency. Fruit thinning is essential for balancing crop load, improving fruit size, and enhancing overall orchard productivity. AI-driven fruit thinning systems utilize machine vision technologies to detect flowers, buds, and immature fruits accurately, enabling selective thinning operations with minimal human intervention. Khanal *et al.*, [25] reported that machine vision systems using YOLO-based object detection achieved high accuracy in detecting flower clusters for precision thinning and pollination operations. Additionally, precision thinning technologies supported by computer vision models improve crop load management while minimizing fruit damage and operational inefficiencies [47].

These applications should nevertheless be interpreted within their species-specific experimental contexts. Evidence that a lightweight vision model performs effectively for fruit, flower, bud, or branch detection in one orchard crop does not establish equivalent performance across other fruit species. Differences in morphology, canopy architecture, occlusion, training systems, growth stages, and orchard-management practices may create substantial domain shifts. Therefore, the literature collectively demonstrates the potential applicability of lightweight vision technologies across diverse fruit-production contexts, rather than demonstrating universal transferability of individual models across species.

The integration of lightweight vision models ultimately contributes to precision agricultural automation by connecting AI, robotics, sensing technologies, and cloud-based analytics into unified smart orchard systems. Precision agricultural automation allows orchard operations such as pruning, fruit thinning, disease detection, yield estimation, and harvesting to be conducted more accurately and efficiently. Recent literature emphasized that smart orchard systems supported by AI and computer vision technologies enhance operational sustainability, optimize resource utilization, and improve overall agricultural competitiveness [8]. Consequently, lightweight vision models are becoming an important technological foundation for future smart orchard development and sustainable fruit tree cultivation.

### *3.2 Pruning and Thinning Efficiency in Sustainable Fruit Cultivation*

Precision pruning and fruit thinning efficiency play a crucial role in improving the sustainability and productivity of fruit tree cultivation. Traditional orchard management practices often rely heavily on manual labor, which is time-consuming, inconsistent, and increasingly challenged by labor shortages and rising operational costs. In contrast, the integration of lightweight vision models, artificial intelligence (AI), and automated orchard management systems has significantly improved pruning and thinning precision, resulting in enhanced fruit quality, operational efficiency, and long-term agricultural sustainability [23,47].

One of the most significant contributions of precision pruning and thinning efficiency is the improvement of fruit yield quality. Proper pruning and thinning practices optimize light interception, air circulation, and nutrient distribution within fruit trees, which directly influence fruit size, color, sweetness, and overall market quality. AI-based vision systems and machine learning technologies enable real-time identification of branches, flowers, and fruits requiring pruning or thinning interventions, thereby improving the accuracy and consistency of orchard management operations. Moreover, machine vision technologies integrated with deep learning models can estimate crop load and determine optimal fruit density, helping growers maintain balanced fruit development and higher commercial value [2].

In addition, precision pruning and thinning technologies contribute significantly toward reducing operational costs in orchard management. Conventional pruning and thinning activities are highly labor-intensive and require experienced workers, resulting in substantial production expenses. Recent studies highlighted that AI-driven robotic pruning and thinning systems can substantially reduce labor dependency and improve operational efficiency through automated decision-making and real-time orchard monitoring [11,23]. Furthermore, AI-assisted orchard management systems have demonstrated the potential to reduce orchard management costs by up to 50% through optimized thinning intensity, improved labor planning, and resource management [42]. These advancements are particularly important in addressing global agricultural labor shortages and improving economic sustainability among fruit growers.

Resource optimisation represents a potential sustainability benefit of AI-enabled precision orchard management, although this benefit should be interpreted according to the specific application of the technology. Lightweight vision models developed for pruning and fruit thinning primarily contribute through improved target recognition, crop-load assessment, canopy analysis, and operational decision-making. Their contribution to reducing chemical inputs is more indirect unless the vision system is integrated with precision application equipment. For example, machine-vision-based orchard spraying systems can identify tree canopies or treatment targets and regulate spraying accordingly, thereby avoiding unnecessary application to non-target areas. Asaei, Jafari, and Loghavi (2019) reported that a machine-vision-based site-specific orchard sprayer reduced chemical consumption by 54% compared with conventional continuous spraying. Similarly, Partel, Costa, and Ampatzidis (2021) demonstrated that a smart tree-crop sprayer integrating artificial intelligence, machine vision, LiDAR, and GPS reduced spray volume by 28% compared with conventional spraying. More recent field evidence has similarly demonstrated substantial reductions in spray volume through machine-vision-based precision spraying systems. These findings suggest that AI-enabled vision technologies can contribute to reduced pesticide application when they form part of a targeted or variable-rate spraying system. Such evidence should not, however, be generalised to imply that lightweight vision models inherently reduce chemical inputs across all orchard applications.

Moreover, precision pruning and thinning efficiency contribute significantly to sustainable orchard productivity. Sustainable fruit cultivation requires balancing productivity, environmental preservation, and economic viability. AI-powered orchard management systems improve the consistency and effectiveness of pruning operations, leading to healthier tree structures, improved crop management, and stable long-term productivity [20,23]. Automated pruning and thinning technologies also support sustainable intensification in agriculture by enabling higher production efficiency without excessive resource consumption or environmental degradation. Consequently, precision orchard technologies are becoming essential tools in modern sustainable fruit farming systems.

Finally, enhanced pruning and thinning efficiency strengthens agricultural competitiveness in both domestic and international fruit markets. High-quality fruits, efficient production systems, and sustainable agricultural practices increase growers' ability to meet market standards and consumer expectations. Smart orchard technologies enable growers to improve production consistency, reduce operational uncertainties, and respond more effectively to changing agricultural demands and climate conditions. Additionally, the adoption of AI-based precision agriculture technologies enhances technological competitiveness and supports the modernization of orchard management systems, positioning fruit growers for long-term resilience and profitability in increasingly competitive agricultural industries.

### *3.3 Mediating Role of Fertilizer Efficiency*

Operational efficiency plays a critical mediating role in linking lightweight vision models and sustainable fruit tree cultivation outcomes. AI-driven operational efficiency enables orchard management systems to perform pruning and fruit thinning activities with greater precision, speed, and consistency, thereby reducing labor dependency and minimizing resource wastage. Through computer vision, machine learning, and real-time image processing, lightweight vision models can accurately identify branches, fruits, and canopy structures requiring pruning or thinning intervention.

These intelligent systems support automated decision-making processes that improve orchard productivity while optimizing the use of labor, fertilizers, water, and energy resources. Recent studies have emphasized that AI technologies significantly improve farming efficiency by enabling data-driven decision-making, predictive analytics, and real-time crop monitoring, all of which contribute to sustainable agricultural practices [4].

Furthermore, AI-driven operational efficiency contributes to sustainable cultivation by improving precision management and reducing unnecessary agricultural inputs. Lightweight vision systems integrated with Internet of Things (IoT) technologies allow orchard managers to conduct targeted pruning and fruit thinning based on actual plant conditions rather than generalized manual estimations. This precision reduces operational errors, enhances fruit quality, and supports balanced tree growth, ultimately improving long-term orchard sustainability. According to Kumari *et al.*, [28], AI-supported smart farming technologies optimize resource utilization through intelligent monitoring systems, predictive algorithms, and automated decision-making, thereby enhancing both productivity and environmental sustainability. Similarly, Hossain *et al.*, [17] reported that AI-powered agricultural systems improve operational efficiency, reduce environmental impacts, and enhance agricultural profitability by supporting efficient resource allocation and smart cultivation practices.

The mechanisms linking smart technologies and agricultural outcomes can also be understood through the integration of precision agriculture principles and intelligent automation systems. Lightweight vision models enhance operational efficiency by reducing the time and labor required for pruning and thinning activities while simultaneously improving the accuracy of orchard management decisions. These technologies generate real-time visual data that can guide precise interventions, enabling farmers to optimize crop growth conditions and improve yield consistency. In addition, AI-driven automation contributes to climate-smart agriculture by minimizing excessive chemical use, reducing waste generation, and supporting environmentally responsible farming systems [19]. Consequently, operational efficiency serves as a strategic mechanism through which lightweight vision models contribute to sustainable fruit cultivation, improved productivity, and long-term agricultural resilience.

### *3.4 Theoretical Implications*

This study contributes to the conceptual development of smart agriculture and precision-orchard literature by bringing together the Diffusion of Innovation (DOI) Theory and Technology Acceptance Model (TAM) as complementary theoretical lenses. The contribution does not lie in claiming a new integration of DOI and TAM, since previous agricultural technology research has combined innovation-diffusion and technology-acceptance perspectives. Rather, the contribution lies in extending this combined theoretical logic from technology adoption toward the subsequent operational pathway through which lightweight vision technologies may generate value in orchard management.

DOI explains how characteristics such as relative advantage, compatibility, complexity, trialability, and observability may influence the attractiveness and adoption potential of lightweight vision technologies. TAM complements this perspective by explaining how users evaluate the usefulness and ease of use of such technologies. Together, the theories provide a basis for understanding the conditions that may facilitate technology acceptance and utilisation. The present framework then extends beyond these traditional adoption outcomes by proposing that effective utilisation of lightweight vision models contributes to sustainable fruit-tree cultivation through improvements in precision pruning and fruit-thinning efficiency.

The theoretical contribution of the study therefore lies in connecting three analytical levels: technological characteristics and user acceptance, operational efficiency, and sustainable cultivation outcomes. Precision pruning and fruit-thinning efficiency are positioned as the mechanism translating technological capability into potential agricultural value. This approach avoids assuming that technology adoption automatically generates sustainability benefits and instead emphasises the operational processes through which such benefits may emerge.

Because the study is conceptual, these theoretical relationships should be interpreted as propositions requiring subsequent empirical examination. Future studies could directly operationalise DOI characteristics, perceived usefulness, perceived ease of use, actual technology utilisation, operational efficiency, and sustainability outcomes to empirically test the complete theoretical mechanism proposed in this study.

### *3.5 Practical Implications*

The integration of artificial intelligence (AI) technologies into orchard management has the potential to significantly transform modern fruit cultivation practices by improving operational efficiency, reducing labor dependency, and enhancing agricultural sustainability. The increasing application of lightweight vision models, computer vision systems, deep learning, and smart sensing technologies enables farmers to perform precision pruning, fruit thinning, crop monitoring, and yield estimation with greater accuracy and efficiency. Recent studies indicate that AI-driven agricultural systems contribute to real-time decision-making, automated orchard monitoring, and optimized resource utilization, which collectively improve orchard productivity and reduce operational costs [14,49]. Furthermore, lightweight AI models are particularly valuable in orchard environments because they can operate efficiently on edge devices and mobile agricultural platforms while maintaining high detection accuracy in real-time field conditions [1].

From a policy perspective, the study highlights the importance of smart farming policy development to support the adoption of AI technologies in orchard management. Governments and agricultural institutions should promote digital agricultural transformation through financial incentives, infrastructure development, agricultural digitization programs, and technical training for farmers. Recent literature emphasizes that smart agriculture policies play an essential role in accelerating the adoption of precision farming technologies, particularly in addressing labor shortages, improving food security, and enhancing environmental sustainability [21,32]. In addition, policymakers should encourage collaboration between agricultural researchers, technology developers, and farming communities to facilitate the commercialization and accessibility of AI-driven orchard management systems.

The study also provides important implications for agricultural modernization strategies. The adoption of lightweight vision models and intelligent orchard systems may support the transition from conventional farming toward data-driven and automated agricultural ecosystems. Smart orchard technologies, including AI-based pruning systems, robotic thinning equipment, machine vision platforms, and IoT-integrated monitoring systems, can improve productivity while minimizing resource wastage and environmental impact [47]. The modernization of orchard management through AI integration may further strengthen agricultural competitiveness, enhance fruit quality consistency, and support long-term sustainable fruit production.

Moreover, the findings suggest that precision fruit cultivation management can be substantially improved through AI-enabled decision-support systems and automated operational technologies.

Precision pruning and fruit thinning allow farmers to optimize crop load, improve fruit size and quality, reduce excessive branch competition, and enhance overall orchard health. Previous studies reported that machine vision technologies and AI-based crop monitoring systems contribute to more accurate fruit detection, branch identification, and intelligent orchard operations, thereby increasing efficiency and profitability in fruit farming [2,25]. Consequently, the integration of lightweight vision models into orchard management systems may represent an important advancement toward sustainable, intelligent, and high-efficiency fruit cultivation practices.

### *3.6 Limitations of Lightweight Vision Systems in Orchard Applications*

Despite their potential advantages for real-time and resource-efficient agricultural applications, lightweight vision systems are subject to several technical and operational limitations that should be considered when evaluating their suitability for precision pruning and fruit thinning. One important limitation is the potential trade-off between computational efficiency and predictive performance. Lightweight architectures generally reduce model size, parameters, memory requirements, and computational complexity to facilitate deployment on resource-constrained devices. However, model compression and architectural simplification may reduce the capacity of the system to extract complex visual features, particularly when agricultural targets are small, partially occluded, visually similar, or distributed within complex canopy environments. Consequently, computational efficiency should not be interpreted as equivalent to operational effectiveness.

A second limitation concerns sensitivity to uncontrolled orchard conditions. Vision systems deployed in outdoor environments must operate under substantial variations in illumination, shadows, weather conditions, camera perspectives, canopy density, foliage movement, background complexity, and seasonal changes. Occlusion represents a particularly important challenge because branches, leaves, flowers, and fruits frequently overlap within orchard canopies. These conditions can reduce detection, segmentation, and localisation performance compared with results obtained from controlled or curated image datasets. For pruning and fruit-thinning applications, recognition errors may be operationally important because inaccurate identification of branches, buds, flowers, or fruits can subsequently affect pruning-point determination, crop-load assessment, or thinning decisions.

A third limitation involves model generalisability and domain shift. Lightweight vision models are commonly developed and evaluated using datasets collected from particular fruit species, cultivars, orchard configurations, geographic locations, growth stages, or imaging conditions. A model demonstrating high accuracy within its original dataset may not maintain equivalent performance when deployed in a substantially different orchard environment. Differences in tree architecture, fruit morphology, branch density, training systems, camera characteristics, and environmental conditions may alter the visual distribution encountered by the model. Therefore, reported model performance should be interpreted within the specific conditions under which training and validation were conducted unless external or cross-domain validation has been demonstrated.

Practical edge deployment also introduces hardware-related constraints. Although lightweight architectures require fewer computational resources than conventional deep-learning models, actual field implementation may still be affected by processor capability, memory availability, battery life, energy consumption, sensor quality, heat management, communication infrastructure, and equipment cost. Techniques such as pruning, quantisation, and knowledge distillation can further reduce computational requirements, but aggressive model compression may affect accuracy or robustness. Evaluation of lightweight agricultural vision systems should therefore consider multiple performance dimensions, including detection accuracy, inference latency, model size, computational demand, energy consumption, and stability under actual field conditions.

Another limitation is that image-based lightweight models may provide incomplete information for complex orchard-management decisions. Precision pruning, for example, may require understanding not only the visual presence of a branch but also its orientation, depth, diameter, connectivity, position within the canopy, relationship with neighbouring branches, and implications for future tree growth. Similarly, fruit-thinning decisions can depend on spatial distribution, crop load, developmental stage, cultivar-specific characteristics, and agronomic objectives. Two-dimensional visual detection alone may therefore be insufficient for fully autonomous decision-making in some applications. Integration with depth cameras, three-dimensional reconstruction, LiDAR, multispectral sensing, temporal information, robotics, or other complementary sensing technologies may be required for more complex operational tasks.

Finally, the practical effectiveness of lightweight vision systems depends on successful integration with the wider orchard-management system. Accurate object detection does not automatically result in successful pruning or thinning. Vision outputs must be translated into appropriate agronomic decisions and, in automated systems, into accurate robotic actions. Errors can consequently arise at multiple stages, including sensing, recognition, decision-making, localisation, motion planning, and physical execution. The performance of a lightweight vision model should therefore not be evaluated solely through algorithmic metrics such as precision, recall, or mean average precision. Field-based evaluation should also consider operational reliability, task completion, intervention accuracy, time efficiency, system robustness, and agronomic outcomes.

These limitations highlight an important distinction between algorithmic efficiency and operational effectiveness. Lightweight models provide substantial opportunities for deploying artificial intelligence on resource-constrained agricultural platforms, but smaller model size and faster inference do not inherently guarantee reliable performance in complex orchard environments. Their practical value for precision pruning and fruit thinning therefore requires balanced assessment of computational efficiency, recognition accuracy, environmental robustness, hardware feasibility, agronomic relevance, and field-level operational performance.

### *3.7 Cross-Species Applicability and Generalisability*

The application of lightweight vision models across different fruit species requires careful qualification because fruit crops differ substantially in their biological characteristics, canopy architecture, cultivation systems, and orchard-management requirements. Although lightweight computer vision models have been developed for different orchard applications, successful performance within one fruit species should not be interpreted as evidence that the same model can be directly transferred to another species. The existing evidence is more appropriately interpreted as demonstrating the potential breadth of lightweight vision applications across fruit cultivation contexts rather than universal cross-species generalisability.

Species-related differences can substantially affect computer vision performance. Apples, pears, peaches, citrus fruits, cherries, mangoes, and grapes differ in fruit size, shape, colour, clustering patterns, foliage density, branch architecture, flowering characteristics, and levels of natural occlusion. Their orchard-training and production systems may also differ considerably. These characteristics influence the visual features that detection and segmentation models must recognise and may consequently affect model accuracy, robustness, and computational performance. A lightweight architecture optimised for detecting a particular fruit, flower, bud, or branch structure may therefore require retraining, fine-tuning, or architectural modification before being applied to another fruit species.

The issue is particularly important for precision pruning because pruning decisions are species- and production-system-dependent. Tree architecture, branch orientation, growth habits, fruiting positions, training systems, and pruning rules vary across fruit crops. Therefore, accurate branch detection alone does not establish that a vision system can determine agronomically appropriate pruning decisions across different species. For example, the visual and structural requirements involved in pruning a cherry tree may differ from those encountered in apple, citrus, peach, or other orchard systems. Vision-based pruning models should consequently be evaluated not only according to their ability to recognise tree structures but also according to whether the resulting decisions are appropriate for the agronomic requirements of the specific crop.

Similar considerations apply to fruit thinning. Fruit-thinning strategies vary according to species, cultivar, flowering characteristics, fruit-set patterns, crop-load targets, developmental stage, and production objectives. Vision systems designed to identify apple flowers or flower clusters, for example, provide evidence for a specific thinning context and should not automatically be assumed to perform equivalently for fruit species with substantially different flowering or fruiting characteristics. Consequently, the effectiveness of lightweight vision models for thinning should be interpreted within the biological and operational context in which the model was developed and evaluated.

Cross-species transfer may nevertheless be possible through approaches such as transfer learning, domain adaptation, model fine-tuning, and the development of diverse multi-species datasets. These approaches may reduce the need to develop completely independent models for every fruit crop. However, their effectiveness should be empirically demonstrated through external and cross-species validation rather than assumed from within-species performance. Evaluation should examine whether models retain acceptable detection accuracy, computational efficiency, inference speed, and operational reliability when transferred to fruit species or orchard environments that differ from their original training conditions.

Accordingly, this conceptual study does not propose that a single lightweight vision model is universally applicable across fruit species. Rather, it proposes that lightweight vision technologies represent a broader technological approach with potential applications across different fruit-production systems, subject to species-specific adaptation and validation. The conceptual relationships proposed in this study should therefore be interpreted at the general theoretical level, while their technological implementation and operational effectiveness remain dependent on the biological, agronomic, and environmental characteristics of individual fruit crops.

### *3.8 Future Research Directions*

Future research should empirically validate the proposed framework by collecting primary data from fruit tree farmers, orchard managers, and agricultural technology users. Although lightweight vision models have shown strong potential in improving real-time detection, image-processing efficiency, and orchard automation, further quantitative testing is needed to confirm their actual influence on precision pruning and fruit thinning efficiency. Recent studies show that computer vision and AI-based systems are increasingly important in precision agriculture, but practical field validation remains essential because orchard environments differ in lighting, canopy density, fruit occlusion, and seasonal conditions [14,50].

Future research should systematically investigate both within-species robustness and cross-species transferability of lightweight vision models. Fruit crops differ in canopy architecture, branch structure, fruit morphology, flowering patterns, foliage density, growth habits, training systems, and pruning and thinning requirements. Consequently, models developed for apples, cherries, pears, citrus, peaches, grapes, mangoes, or other fruit crops should not be assumed to provide equivalent performance when transferred between species. Future studies should employ external validation datasets and cross-species experimental designs to determine the extent to which model performance declines under domain shift. Research should also examine whether transfer learning, domain adaptation, fine-tuning, or multi-species training datasets can improve model portability while preserving the computational advantages of lightweight architectures. Such evidence is necessary before broad claims regarding cross-species applicability or scalability can be established.

In addition, future research should explore the integration of lightweight vision models with robotics, drones, and Internet of Things (IoT) systems. The combination of machine vision, smart sensors, autonomous robots, drones, and cloud-based analytics can support real-time orchard monitoring, automated pruning, fruit-load estimation, thinning decisions, and yield prediction. Recent studies highlight that IoT-enabled sensors and smart farming systems can improve data-driven decision-making, optimize resource use, and support agricultural sustainability [29,33]. Therefore, future studies should examine how lightweight vision models can be embedded into robotic pruning platforms, drone-based orchard mapping, and IoT-based farm management systems.

Future research should place greater emphasis on evaluating the trade-off between model efficiency and field-level robustness. Comparative studies should assess lightweight architectures not only through conventional metrics such as precision, recall, F1-score, and mean average precision, but also through model size, inference latency, memory requirements, energy consumption, and performance on actual edge hardware. More importantly, models should be evaluated under challenging orchard conditions involving variable illumination, occlusion, dense canopies, different viewing angles, weather variation, and seasonal changes. External validation across independent orchards and datasets is necessary to determine whether reported performance represents genuine model generalisability rather than dataset-specific optimisation.

Finally, longitudinal studies are needed to assess the long-term effects of lightweight vision models on orchard productivity, labor efficiency, fruit quality, cost reduction, and sustainable cultivation. Most existing studies focus on model accuracy or short-term technical performance, while fewer studies examine whether these technologies produce consistent economic and environmental benefits over several growing seasons. Longitudinal research would allow researchers to observe adoption patterns, learning effects, maintenance challenges, farmer acceptance, and long-term return on investment. Such studies would provide stronger evidence for policymakers, agricultural engineers, and fruit farmers in deciding whether lightweight vision models should be scaled up for sustainable orchard management.

## 4. Conclusions

This study develops a conceptual framework explaining how lightweight vision models may contribute to sustainable fruit-tree cultivation through improvements in precision pruning and fruit-thinning efficiency. The central argument is that the value of lightweight vision technologies extends beyond computational efficiency and real-time detection capability. When effectively utilised in orchard operations, these technologies may support more accurate pruning and thinning decisions, improve labour and time efficiency, optimise crop-load management, and strengthen overall orchard-management performance. Precision pruning and fruit-thinning efficiency are therefore positioned as the operational mechanism through which lightweight vision technologies may contribute to sustainable cultivation outcomes.

The study also draws upon the complementary perspectives of the Diffusion of Innovation (DOI) Theory and Technology Acceptance Model (TAM). DOI provides a basis for understanding how innovation characteristics may influence the adoption of lightweight vision technologies, while TAM explains how users evaluate their usefulness and ease of use. The conceptual contribution lies in extending this adoption-oriented theoretical logic toward an operational pathway in which technology acceptance and effective utilisation are connected with pruning and thinning efficiency and, subsequently, sustainable fruit-tree cultivation. This perspective emphasises that the adoption of lightweight technologies alone does not automatically generate sustainability benefits; such benefits depend on their effective application within orchard-management processes.

As a conceptual study, the proposed relationships require empirical validation. The applicability of lightweight vision systems may vary according to fruit species, cultivar, canopy architecture, orchard-management system, environmental conditions, technological infrastructure, and model characteristics. Future research should therefore test the proposed framework across different fruit crops and production environments and evaluate whether improvements in computational and operational efficiency translate into sustained economic and environmental benefits under actual field conditions. Overall, the framework provides a theoretical basis for further investigation of how resource-efficient AI technologies can support more precise, efficient, and sustainable orchard-management systems.

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**Author Contributions Statement**
Author 1 was responsible for the conceptualization of the study, literature review, framework development, data interpretation, and manuscript drafting. Author 2 contributed to the theoretical development, methodology design, critical revision of the manuscript, and supervision of the overall research direction. Author 3 assisted in the analysis of agricultural technology adoption literature, refinement of the research framework, and manuscript editing. Author 4 contributed to the discussion on willingness to pay, policy implications, and final manuscript preparation. Corresponding Authors (Author 5 and Author 6), as research supervisors, provided academic supervision, methodological guidance, critical review, and overall validation of the study. All authors have read and approved the final version of the manuscript for publication.

**Generative AI Declaration**
During the preparation of this work, the authors used ChatGPT (OpenAI) solely to enhance the clarity, grammar, and readability of the manuscript. All generated outputs were critically reviewed, verified, and revised by the authors. The authors accept full responsibility for the accuracy, integrity, and originality of the content presented in this publication.

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