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# SMART FRUIT GROWING THROUGH DIGITAL TWIN PARADIGM: SYSTEMATIC REVIEW AND TECHNOLOGY GAP ANALYSIS

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ABSTRACT
This article provides a systematic review of innovations in smart fruit-growing. The research aims to highlight the technological gap and define the optimal studies in the near future moving toward smart fruit-growing based on a systematic review of literature for the period 2021–2022. The research object is the technological gap until the smart fruit-growing. The research question of the systematic review was related to understanding the current application of vehicles, IoT, satellites, artificial intelligence, and digital twins, as well as active studies in these directions. The authors used the PRISMA 2020 approach to select and synthesise the relevant literature. The Scopus database was applied as an information source for the systematic review, completed from 10 May to 14 August 2022. Forty-three scientific articles were included in the study. As a result, the technology gap analysis was completed to highlight the current studies and the research trends in the near future moving toward smart fruit-growing. The proposed material will be useful background information for leaders and researchers working in smart agriculture and horticulture to make their strategic decisions considering future challenges and to optimise orchard management or study directions. Considering the current challenges, authors advise paying attention to decision-making, expert, and recommendation systems through the digital twin paradigm. This study will help the scientific community plan future studies optimising research to accelerate the transfer to new smart fruit-growing technologies as it is not sufficient to develop an innovation, but it must be done at the appropriate time.

KEY WORDS
**artificial intelligence, digital twin, smart horticulture, orchard, remote sensing**

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## INTRODUCTION

Modern horticulture faces a series of global challenges, such as climate changes and yield quality, thus leading to competitiveness and economy of production issues and the public's demand for sustainable and safe food. Often, the mitigation of these challenges requires contradictory solutions, e.g., the ability to limit the increasing disease pressure while ensuring environmentally friendly growing. Applying balanced cultivation solutions requires knowledge, a high level of expertise in growing the relevant

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horticulture crop, and continuous access to timely environmental and market information. One of the solutions is smart horticulture, which includes management of publicly available data, locally collected sensor data, decision-making and advisory systems. An essential part of such a smart horticulture system is the development of a digital twin of orchards and the use of unmanned aerial vehicles (UAV) for their constant monitoring (Van Der Burg et al., 2021; Verdouw et al., 2021). This development direction can strengthen existing horticulture farms and promote their development and economic competitiveness while ensuring the environment's and society's requirements.

In the Green Deal of the European Union (European Commission, 2019), the Biodiversity Strategy (European Commission, 2020) defines future development perspectives, and both documents directly affect the agricultural sector. The achievement of strategic goals requires promoting innovations in the agricultural sector, ensuring the efficient use of resources, reaching the maximum harvest volumes and reducing the negative impact of weather conditions on the agricultural harvest. The application of information technology in the agricultural sector using innovative technologies will ensure the future development of this sector, obtaining the maximum amount of harvest with as few resources as possible (European Commission, 2019; 2020).

A comprehensive analysis-based systematic review of literature related to orchard management with small unmanned aerial vehicles (UAV) was presented by Zhang et al. (2021). All research related to UAV application in fruit growing was grouped into five categories: (1) resource efficiency, (2) geometric traits, (3) productivity, (4) disease, and (5) other applications. Each category was discussed in detail and analysed from four aspects, namely, (1) sensors, (2) methods, (3) decision indicators, and (4) orchard management activities, providing conclusions about future research and its relevance. Evaluating potential future research, Zhang et al. (2021) outlined challenges, some of them could face: (1) most research focused on specific fruit species at a certain growth stage under certain conditions; (2) despite the promising results in deep learning, further progress in improving the performance of proposed methods in various environmental and agronomic conditions with advanced deep learning algorithms need to be undertaken; (3) current achievements in indirect yield estimation are positive; however, there is abundant room for further progress in enhancing the robustness of the methods and performance for different crops and growing stages remain unanswered at present; (4) techniques like machine learning and deep learning have not been adequately employed in UAV orchard management; (5) UAVs are currently operated by persons with the skills of professional pilots; (6) powerful UAVs are generally more costly and not affordable for applications, especially in developing countries; and (7) real-time direct estimation of fruits is encouraged.

On the other hand, artificial intelligence application in orchard management has been presented in a review of deep learning application for fruit detection and yield estimation by Koirala et al. (2019). The review presents the description of vertical progress in deep learning: (1) architectures; (2) feature extraction; (3) training, tuning and testing; (4) transfer learning, augmentation, and datasets; and (5) yield estimation. It summarises that research is completed around R-CNN and YoLo architectures, applying a regression model for yield estimation. It is suitable to mention a review presented by Hasan et al. (2020), which grouped challenges into three categories: (1) public data availability and their quality improvement; (2) enhancement of deep learning methods; and (3) quality control. That coincides with research tasks outlined by the "Trustworthy AI" concept.

Two years later to the review by Hasan et al. (2020), it would be expected to find research progress and outline new state-of-the-art considering the rapidly growing global artificial intelligence market (Grand View Research, 2022), as well as the worldwide inclusion of artificial intelligence into research strategies and a list of key enabling technologies. Particular interest was expressed in applying the digital twin paradigm for autonomous orchard management based on key enabling technologies like artificial intelligence and robotisation.

Making an analogy to the most challenging research field, "autonomous cars", the automatisation of orchard management will be iterative. Six levels of driving automation are defined in "ISO/SAE PAS 22736:2021 Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles" starting from "Level 0: No Driving Automation" until "Level 5: Full Driving Automation". The evolution of orchard management may have a similar pattern, where traditional fruit growing is firstly supported by precise horticulture, followed by smart horticulture through iterative automatisation, solving technological and legal issues. For example, if the autonomy of a UAV is supported

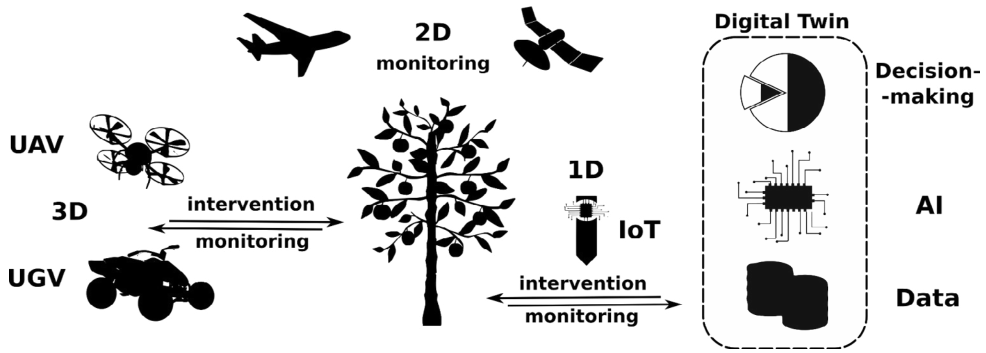


Fig. 1. Digital twin of smart fruit-growing

technologically, their application is restricted for safety reasons and social unreadiness to use these new technologies. Meanwhile, the digital twins have similar integration levels: (1) digital models; (2) digital shadows, which support monitoring of physical entities; and (3) digital twins, which provide bidirectional communication between virtual and physical entities (Botín-Sanabria et al., 2022).

The schematic presentation of a smart fruit-growing system is provided in Fig.1. Here, a digital twin is considered software for orchard management, which provides an interface between a fruit-grower, a virtual entity and a physical entity working like a decision-making tool or a command centre. The development of a digital twin of smart fruit growing depends on technological readiness. If yield estimation is a domain of precise horticulture related to monitoring and prediction, smart fruit growing implies interventions based on data-driven decision-making. Therefore, the authors reviewed the technology gap from yield estimation to smart fruit growing because each computer decision requires data before launching some interventions.

Thus, the main research question is, "How big is the technology gap between autonomous fruit yield estimation and smart fruit growing?".

Gap analysis has been applied to many different fields. Accordingly, there are various approaches to gap analysis, where core differences rest with the kinds of gaps in question. Gap analysis consists of four steps: (1) identifying key needs of the present situation, (2) determining the ideal future or desired situation, (3) highlighting the gaps that exist and need to be filled, and (4) modifying and implementing plans to fill the gaps (Kim & Ji, 2018).

As a result, the following research questions (RQ) must be answered first to achieve the main goal:

RQ1: What are the technological solutions and applications of vehicles, IoT and satellites?

RQ2: What are the trends and methods of artificial intelligence application?

RQ3: What are the technological solutions, applications, and challenges of digital twins?

Based on defined questions, the next tasks are identified: (1) to study the current application of vehicles; (2) to study the current application of IoT; (3) to study the current application of satellites; (4) to study the current application of artificial intelligence; (5) to study the current application of digital twins; and (6) to discuss the results.

Then, it will be possible to highlight research challenges to overcome the technology gap to achieve smart fruit-growing.

# 1. Research methods

To achieve the goal and answer research questions, the authors used the PRISMA 2020 approach. The Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) statement was designed to help systematic reviewers transparently report why the review was done, what the authors did, and what they found. The PRISMA 2020 is an updated guideline for reporting systematic reviews, which includes reporting guidance that reflects advances in methods to identify, select, appraise, and synthesise studies. The structure and presentation of the items have been modified to facilitate implementation (Page et al., 2021).

The process of selecting and synthesising the relevant literature is shown in Fig. 2, that is, a PRISMA 2020 flow diagram.

Systematic literature reviews can be defined as a means of identifying, evaluating, and interpreting all available studies relevant to a specific research question, domain, or phenomenon of interest (Kitch-

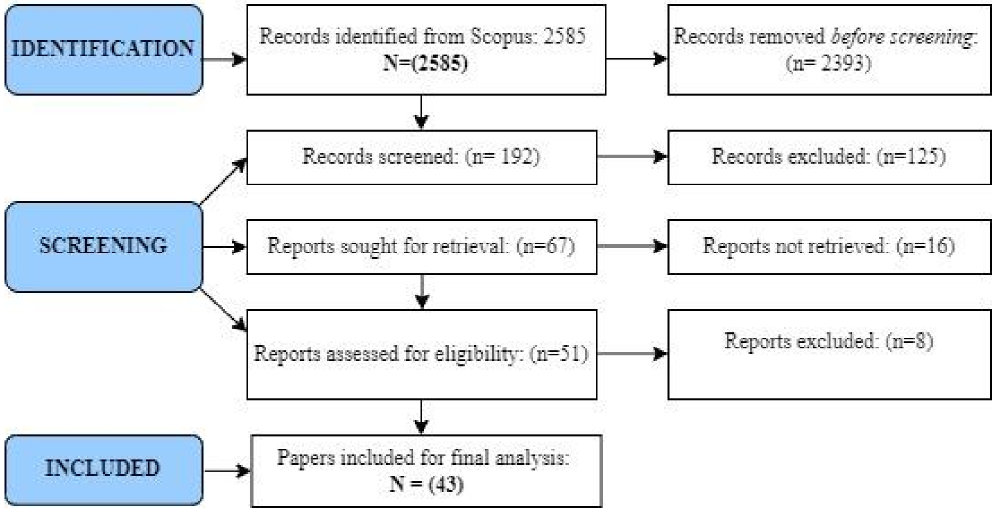


Fig. 2. PRISMA 2020 flow diagram for new systematic literature reviews

Tab. 1. Criteria and results of the relevant literature search

| Topic | Keywords | Selection criteria and results | |
|---|---|---|---|
| Vehicles | (horticulture OR precision AND agriculture OR smart AND farming OR orchard AND management OR yield AND estimation OR fruits) OR (uav OR ugv OR uuv OR usv OR artificial AND intelligence OR deep AND learning OR object AND detection OR digital AND twin OR digital AND shadow): 474 | 2021-2022: 144 | Review & articles: 42 |
| | | Records screened: 42 | Sought for retrieval: 17 |
| | | Eligible: 12 | Final analysis: 12 |
| IoT | (sensor OR sensors OR iot OR “Internet of Things” ) AND (orchard OR horticulture): 1370 | 2021-2022: 255 | Review & articles: 128 |
| | | Records screened: 79 | Sought for retrieval: 22 |
| | | Eligible:15 | Final analysis: 10 |
| Satellites | (satellite OR satellites) AND (“yield estimation” OR “yield prediction” OR “yield monitoring”) AND (orchard OR horticulture): 318 | 2021-2022: 112 | Review & articles: 89 |
| | | Records screened: 10 | Sought for retrieval: 8 |
| | | Eligible: 7 | Final analysis: 4 |
| Artificial intelligence | (horticulture OR orchard) AND (“yield prediction” OR “yield estimation”) AND (“artificial intelligence” OR “deep learning” OR “machine learning”) AND fruit: 200 | 2021-2022: 94 | Review & articles: 84 |
| | | Records screened: 11 | Sought for retrieval: 10 |
| | | Eligible: 9 | Final analysis: 9 |
| Digital Twin | “digital twin” AND “smart farming”: 223 | 2021-2022: 180 | Review & articles: 50 |
| | | Records screened: 50 | Sought for retrieval: 10 |
| | | Eligible: 8 | Final analysis: 8 |
| | **Total: 2585** | **2021-2022: 785** | **Review & articles: 393** |
| | | **Records screened: 192** | **Sought for retrieval: 67** |
| | | **Eligible: 51** | **Final analysis: 43** |

enham, 2004). A quality literature review takes time. Authors not only need to collect literature but also require in-depth understanding and relevant experience in the specific field because the interpretation of the results of the studies included in the literature review is more subjective (Fisch & Block, 2018).

The authors used the SCOPUS database to identify and select research papers. The authors chose this database because it has a large amount of indexed data, includes only well-performing, high-impact and peer-reviewed journals, and is convenient for data selection. Records identified in the Scopus database were sufficient to obtain a significant data sample size, so no additional databases were required.

In the first step, review topics based on research questions were assigned, and in the second step, the most appropriate keywords were selected for each topic (Table 1).

In total, 2585 results were found using the above-mentioned keywords. To identify all appropriate papers on the selected topics, the authors used the advanced search technique and selected "reviews" and "articles" from 2021 to 2022. Within each topic section, the titles and abstracts of the reviews and articles were examined, and duplicates and articles unrelated to the topic were excluded. Then, the authors read and evaluated the remaining 192 articles. As a result, 43 articles were selected for in-depth analysis.

## 2. Research results

The systematic review results are presented independently for each research question related to the current application of (1) vehicles, (2) IoT, (3) satellites, (4) artificial intelligence, and (5) digital twins.

### 2.1. Current application of vehicles

Tardaguila et al. (2021) completed an analysis of vehicle-mounted platforms: (1) ground vehicles, (2) aerial vehicles, and 3) portable platforms. Different sensors were mounted and researched, and such technologies as GPS and RTK provide a sufficient platform for vehicle navigation. Unmanned vehicles are discussed; however, monitoring of orchards as a whole autonomous system is not sufficiently studied.

Unmanned systems, such as unmanned ground vehicles (UGV) and UAVs, provide great support in different fields of application and environment. However, the type of vehicle and the field of application depend highly on the sensors and devices mounted on it. Each vehicle type has its benefits and disadvantages, e.g., UAVs are mostly limited in the weight of payload they can carry. UGVs can carry a heavier load but are limited in mobility compared to UAVs.

A review, "Sensors and Measurements for Unmanned Systems: An Overview" (Balestrieri et al., 2021), depicts fields of application for different vehicle types and environmental factors that can affect vehicle performance and longevity.

The use of UGV in agriculture has a wide range of applications. Most commonly, UGV is used as a device for fruit harvesting. It can be a claw that picks apples from trees (Chen et al., 2021b) and is controlled by AI or carefully designed scissors used for precise grape harvesting (Kolhalkar et al., 2021).

The use of UAVs in agriculture increases as demand for higher quality and higher productivity continues to rise. The main use of UAVs is depicted in articles:

- "Early Estimation of Olive Production from Light Drone Orthophoto, through Canopy Radius" (Ortenzi et al., 2021);
- "Estimating Evapotranspiration of Pomegranate Trees Using Stochastic Configuration Networks (SCN) and UAV Multispectral Imagery" (Niu et al., 2022);
- "An Automatic UAV Based Segmentation Approach for Pruning Biomass Estimation in Irregularly Spaced Chestnut Orchards" (Di Gennaro et al., 2022).

The main UAV application mentioned in the articles is data acquisition while performing the main UAV task, i.e., imaging or remote sensing (Ortenzi et al., 2021; Di Gennaro et al., 2022; Niu et al., 2022).

Images may differ from case to case based on UAV type and mounted sensors, as some UAVs can add special cameras, e.g., multispectral cameras (Niu et al., 2022). A more versatile UAV version is shown in "Identification of fruit tree pests with deep learning on an embedded drone to achieve accurate pesticide spraying" (Chen et al., 2021a), where an AI system is placed on a UAV, allowing it to do image analysis during flight. Based on analysis results made by AI, the path for pesticide spraying is marked for another UAV to do precise pesticide spraying while reducing pesticide effect on healthy trees. For more insight, review articles "Orchard management with small unmanned aerial vehicles: a survey of sensing and analysis approaches" (Zhang et al., 2021) and "A Review on Drone-Based Data Solutions for Cereal Crops" (Panday et al., 2020) show a possible use of a UAV that was not applied or considered in other articles. The review looked into different types of drones and areas of application. As a result, the number of articles reviewed is larger, and the scope of the review is much broader.

AV and UGV are types of vehicles with already defined common constructional designs. UAVs are designed on the same principle as helicopters or planes. UGV have wheels or caterpillar tracks. However, there are attempts in robotics to move away from common construction designs for UAVs and UGVs. A review, "Bio-Inspired Robots and Structures toward Fostering the Modernization of Agriculture" (Kondoyanni et al., 2022), looks into new designs of unmanned vehicles with designs inspired by nature's creations. In 2021, researchers created a miniature robot that mimicked bees, with the main task of miniature robot bees to complement work done by natural bees (Kondoyanni et al., 2022).

## 2.2. Current application of IoT

Even the slightest changes in the environment can influence yield in horticulture; thus, close monitoring of all potential factors is essential. As such, the Internet of Things (IoT) is a highly efficient solution to solving this task. In the context of this review, sensor technology was mainly investigated, as sensors are devices that can be applied in various situations. In a review, "A comprehensive review of remote sensing platforms, sensors, and applications in nut crops" (Jafarbiglu & Pourreza, 2022), the authors have researched various sensor technologies and applications. For example, the review mentions simple sensors planted on or in the ground, as well as, specialised platforms equipped with different sensors, or mobile platforms like UAVs and UGVs with sensors connected to the Internet to transmit data (Abdul Haleem et al., 2022).

Data received from sensors is analysed and used for further studies (Akhter & Sofi, 2021) and real-time adjustments (Rehman et al., 2022).

The range of sensors used in agriculture is wide, starting with clip-type cameras used to monitor plants and predict optional time for harvesting based on images (Lee et al., 2022) and ending with more unusual IoT solutions, like tilt sensors. They are not common in agriculture, but they can be used for danger warnings in locations with potential high-intensity storms or hurricanes (Hui et al., 2022).

One of the main factors that influence yield is irrigation, as plants require the correct amount of water, and it is highly inadvisable to deviate from that. Several different sensor types are used to monitor and react to changes in soil or air. The simplest solution to measure moisture in air is weather stations. They already support various sensors, including moisture, temperature, wind speed and direction sensors (Quezada et al., 2021). It is possible to react to high temperatures or strong winds using all these sensors. Of course, setting up a full meteorological station may not be the best solution for every orchard, so specific sensors can be set up for monitoring moisture, be those temperature sensors or moisture sensors in one form or another. A good example of a temperature sensor use is provided in the article "Intelligent Spraying Water Based on the Internet of Orchard Things and Fuzzy PID Algorithms", where the temperature difference between day and night was a factor for when and how much water should be sprayed for better sugar accumulation in fruits (Zhang et al., 2022). Other solutions that can be used for irrigation systems may contain a soil electrical conductivity sensor (Gao et al., 2021) or an air humidity sensor (Kun et al., 2021).

## 2.3. Current application of satellites

The traditional remote sensing approach used in agriculture is based on the application of satellites. Compared to UAVs, a satellite is a space-based platform suitable for surveying large areas and monitoring national and regional agricultural changes. Satellites provide useful information for assessing the monitored object and its ecosystem at a macro level using different indices. Indices are effective in the case of low spatial-resolution images. UAVs are the optimal remote sensing technique for local agricultural surveys and rapid handling of local agricultural production problems while directly monitoring objects, which must be extracted from the background using computer vision techniques. Thematic mapping is the keyword which best describes the applied purposes of satellites. Macro analysis through maps is interfaced with time-series analysis, change detection, anomaly detection, feature fusion and monitoring of phenology cycle information. For example, Toosi et al. (2022) presented an automatic citrus orchard mapping method using spectral satellites. The developed method was applied for 2016–2019 to analyse land-use changes. Macro monitoring is useful for the public sector when information about a large territory must be collected centrally, but crowdsourcing methods are not allowed or possible. Ali et al. (2022) presented a review of remote sensing applications in yield estimation and prediction. They discussed (1) satellites and spatial resolution, (2) spectral bands, and (3) grouped methods by sensor type. Four forms of vegetation reflectance were mentioned, each with its own set of works: (1) reflectance of individual plant parts (single organ pigments), (2) reflectance of sets (canopies), (3) plant presence and status, and (4) set structure and texture. In the meantime, Tardaguila et al. (2021) grouped smart viticulture applications in different study domains, which can be generalised for other cultures too: (1) soil properties and soil quality assessment; (2) vegetative growth, nutritional status and canopy architecture; (3) pest and disease detection and management; (4) water status; (5) yield components and crop forecasting; (6) fruit composition and quality attributes; (7) targeted management; and (8) selective harvesting. Maybe the principles and techniques for satellite imagery are well-known and researched. However, the development of monitoring systems is an actual research field because algorithms and methods must be tuned for each plant cultivar and its ecosystem. For example, Mwinuka et al. (2021) researched the assessment of canopy water status and yield prediction of irrigated African eggplant tuning prediction models using field survey data.

## 2.4. Current application of artificial intelligence

Speaking about yield estimation, Maheswari et al. (2021) presented a review of intelligent fruit yield estimation for orchards using deep learning-based semantic segmentation techniques. The review does not differ much from the situation mentioned in the review by Koirala et al. (2019), which mentions improvement of deep learning and quality of datasets as driving forces. A more comprehensive review was provided by Fu et al. (2022). The review included the analysis of (1) indirect yield prediction, which was divided into two parts: input features and regression algorithms, and (2) direct yield estimation, which was divided into three parts for analysis, which includes estimation platforms, method of fruit detection and fruit-counting approaches. It closed some significant information gaps, such as the application of the RGB-D sensor and LiDAR or more modern object detection algorithms, like YOLOv4. Additionally, it provided a good roadmap of research fields of AI-based yield estimation. Considering the more recent publications related to accuracy, confidence and recognition quality, Wang and He (2021) applied YoLov5 and experimentally compared it with state-of-the-art CNN architectures using natural dataset and tuning methods. As for specific domain problems, like double counting of fruits, Mirhaji et al. (2021) experimentally evaluated the impact of photographing locations and the number of images on accuracy results. They also applied augmentation that simulates shadows and sunshine. In the meantime, Gao et al. (2022) and Fu et al. (2022) presented research suitable for fruit harvesting: (1) real-time fruit detection from video using YOLOv4-tiny and Kinect V2; and 2) detection of banana stalks using YOLOv4. Meantime, Xia et al. (2022) applied CenterNet, which detects centre-points of objects, and the Kuhn–Munkres algorithm for object tracking. Anderson et al. (2021) analysed autonomous estimation of fruit load in complex terms of business processes in the field: distance to a tree, daytime, cultivars, and others, completing an experiment using a prototype of a UGV. For example, they conclude that a multi-view technique is recommended for fruit load estimation of orchards using the canopy management systems of conventional, hedge and single leader, but not trellised canopies. Summarising the above, the following development vectors can be identified: (1) experimentation with new CNN architectures; (2) if new CNN architecture is not published, the pre-processing or post-processing algorithms are applied to improve accuracy; (3) object tracking application to precise the fruit load; (4) searching for the optimal number and position of imaging points, including video application; (5) experimentation with different cultivars; and (6) designing autonomous vehicle movement and imaging process and its impact on fruit detection accuracy.

## 2.5. Current application of digital twins

The digitalisation level of food production management and the integrity of physical and virtual systems can be classified into three stages of its development: (1) a digital model — an approach with manual data transfer; (2) a digital shadow with automatic data transfer; and (3) a digital twin, providing a user with a possibility to control the physical system through its virtual representation (Botín-Sanabria et al., 2022). If the digital shadow is associated with precision agriculture, smart farming will be the next generation related to food production automation, in which management tasks are not only based on geospatial data but also on context data, situational awareness and event triggers, using a digital twin approach constructing a cyber-physical system for farm management (Verdouw et al., 2021).

Digital twin architecture has been introduced for Controlled Environment Agriculture applications to optimise productivity through the application of climate control strategies and treatments related to crop management (Chaux et al., 2021). A review of 300 publications on digital twin applications in the food industry concluded that the application of digital twins mainly focuses on the production and processing stages of agriculture, and only several publications consider autonomous control or providing recommendations to humans (Henrichs et al., 2021). A digital twin of a plant in combination with a conceptual ontological model for domain knowledge representation is used to model plant development stages and forecast crop yield considering weather conditions, climate and external events (Skobelev et al., 2021). Pylianidis et al. (2021) identified several use cases for prototyped or deployed digital twins in agriculture in publications dated from 2017 to 2020: digital twins of (1) picked mango fruit that captures its temperature variability and biochemical response throughout the cold chain to evaluate quality losses along the cold chain like firmness and vitamin content; (2) a field using data coming from ISOBUS sensors, other field related data, human expertise and machine learning to provide better field prognostics and act faster in the presence of predicted deviations; (3) to emulate the use of unmanned ground vehicles in fields. It contains a predefined selection of commercially available unmanned ground vehicles which a farmer can test on the virtual field to find the most efficient for their case; (4) a self-contained aquaponics production unit; the purpose of this digital twin is to balance the fish stock and plants in the unit by monitoring them and controlling the unit automatically; (5) a harvested potato to gain insight into harvester damage to potatoes; (6) a tree and its surroundings in an orchard; these digital twins allow the continuous monitoring of orchard production systems to predict stress, disease and crop losses, and develop a self-learning system; (7) any agricultural entity, using holographic devices, augmenting the world with camera-based imaging, placing 2D or 3D content in the real world, simulating them, and creating logs and maintenance events; (8) the cultivated landscape for supporting planners in designing agricultural road networks; (9) that allows users to identify pest and diseases in plants; (10) a field and its machinery, which allows the real-time monitoring of machines and their energy consumption and evaluation of the economic efficiency of the crop management treatment; (11) olive trees to monitor olive fly occurrence; (12) bee colonies, which allows the beekeepers to manage the food storage reserves, to identify disease and pest infections, to inspect if queenless and swarming states exist, it provides an anti-theft mechanism, and insight into the colony status and hygiene; (13) a vertical farm; the virtual and physical components are interconnected through sensors embedded in the materials of the farm structure that monitor temperature, humidity, luminosity, and CO2; (14) the world's agricultural resources; the digital twin will give instant access to critical data on the world's farmland; it will allow sharing insights, materials, and connection with the food supply chain; (15) an indoor garden that calculates the ideal conditions for plants to grow; (16) for aquaculture combining human intelligence and artificial intelligence to help fishermen develop accurate digital decision-making processes for production management. Sung and Kim (2022) proposed a three-layer (physical world, communication protocol and cyber world) architecture for digital twin-based smart farms and the realisation of the conceptual model at the laboratory level.

Several challenges in implementing digital twins have been identified: (1) combining multidisciplinary knowledge and providing enough data (Henrichs et al., 2021); (2) seamless access to object data while maintaining data integrity, respecting use rights, safety and security; (3) real-time synchronisation in rural areas; (4) granularity of digital twins: finer granularity (up to individual plant or animal) increases cost, but provide more value; (5) stakeholders can contribute different types of data and may need only a limited amount of information, which requires a secure and trusted way to access the digital twin (Verdouw et al., 2021); (6) data management, data privacy and security, data quality, real-time communication of data and latency, physical realism and future projections, real-time modelling, continuous model updates, modelling the unknown, transparency and interoperability, large scale computation, and interaction with physical assets (Rasheed et al., 2020).

Enabling technologies are employed to overcome the challenges. These have been categorised into five categories by Rasheed et al. (2020): (1) physics-based modelling, consisting of experimental modelling, three-dimensional modelling and high fidelity numerical simulators; (2) data-driven modelling, consisting of data generation, data pre-processing, management and ownership, data privacy and ethical issues, machine learning and artificial intelligence; (3) big data cybernetics, consisting of data assimilation, reduced order modelling, hardware and software in the loop, other hybridisation techniques, physics-informed ML, compressed sensing and symbolic regression; (4) infrastructure and platforms consisting of big data technologies, IoT technologies, communication technologies, computational infrastructures, digital twin platforms; (5) human-machine interface consisting of augmented and virtual reality, natural language processing, and gesture control.

## 3. Discussion of the results

Based on the systematic review results, this research team identified keywords for each topic (Appendix I). The keywords were grouped into two categories: "application" and "active research". One category identifies the application of study results, another — actual problems and studies mentioned in the literature of 2020–2022.

A fishbone diagram is an effective tool for gap analysis to depict all impact factors, grouping them by categories. It was applied to visualise the review results mentioned in the table of Appendix I (Fig. 3). The keywords were determined using the brainstorming method when the authors completed the systematic review.

The fishbone diagram (Fig. 3) depicts current studies and problems which are already studied. However, it is important to make future forecasts for strategic development. The "research" industry is not an exception; therefore, actual challenges for research in increasing the capacity of smart fruit-growing must be investigated. In other words, the technological gap to the increased capacity of smart fruit-growing must be identified.

Jia (2021) raised the topic of methodology development to plan and design smart gardens because the construction of smart garden projects requires the coordination of multiple disciplines, relying on the support of advanced technologies like IoT. The methodology of smart garden planning and design must provide knowledge, tools and assistance to solve such tasks as (1) correctly selecting radio frequency modules; (2) selecting optimal locations of gateways; (3) data modelling, data processing and visualisation; (4) performance analysis and tuning of algorithms. Jia (2021) highlights five parts of smart garden architecture: (1) smart garden infrastructure, (2) smart garden perception platform, (3) smart garden cloud platform, (4) smart garden data platform, and (5) smart garden application system. Meanwhile, the industrial planning in the farmstead shall be based on the basic principle of ecological and environmental protection, considering economic and social benefits, constantly improving the industrial chain, realising the multiple values of products, promoting their synergistic development, and maximising overall benefits. This is similar to the principles of the "enterprise engineering" discipline. Therefore, it can be concluded that the design of a smart orchard is enterprise engineering of the fruit-growing domain. Kalyanaraman et al. (2022) presented a transdisciplinary coalition called the AgAID Institute, which proposes a new knowledge transfer model and fosters partnerships among agriculture and artificial intelligence researchers, educators, extension professionals, industry technology providers, growers, crop consultants, managers, and policymakers, creating an ecosystem for driving the Agriculture 4.0 revolution. The AgAID Institute is organised around three Ag-inspired research thrusts that work hand-in-hand with three foundational AI research thrusts: (1) forecasting intelligence, (2) farm operations intelligence, and (3) labour intelligence, supported by AI, respectively, (1) interactive data-driven modelling, (2) interactive decision and action support, and (3) Human–AI workflow. Additionally, the AgAID Institute supports knowledge society drivers: (1) circular learning, (2) early adopter network, and (3) adoption

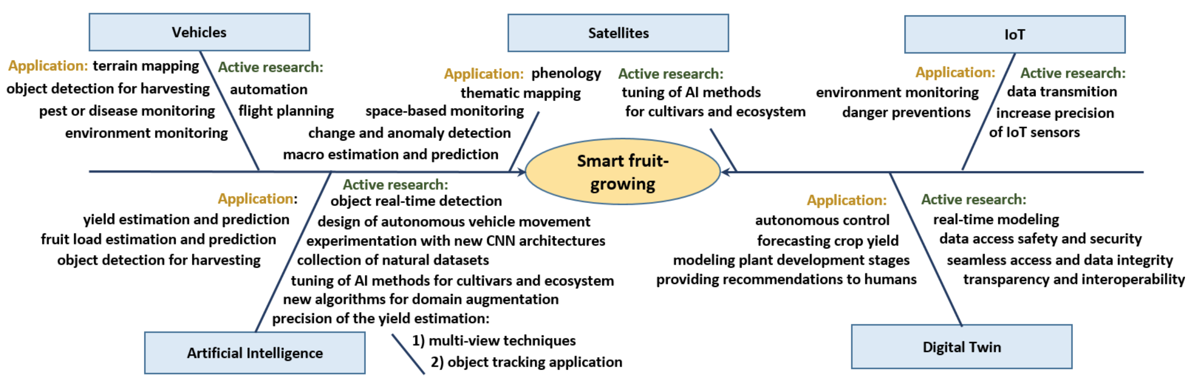


Fig. 3. Actual application and active studies in smart fruit-growing

amplification. Considering challenges, the AgAID Institute raises attention mainly to social, economic, and legacy barriers that coincide with the trustworthy AI concept. Indeed, smart farming technologies are advanced enough; however, the knowledge and innovations are researched independently, and their systematisation in a unified engineering discipline is required. For example, De Alwis et al. (2022) summarised knowledge about smart farming through the big data concept: (1) data types, (2) big data applications, and (3) big data techniques. Meantime, Mohamed et al. (2021) generalised research through IoT, looking at drones and robots like mobile IoT networks, but the application was grouped through sensors. They highlight the importance of Smart Decision Support System development, which can support the real-time analysis and mapping of soil characteristics, also helping to make proper decision management. Finally, they mention that smart agriculture in developing countries needs more support from governments at the level of small farms and the private sector. All these research efforts show the technological gap, which is expressed in the lack of data-driven decision-making systems and the mastership to design smart farming systems for them. Jerhamre et al. (2021) completed a semi-structured interview study in Sweden examining how different agricultural stakeholders regard smart farming technology. They identified the following challenges: (1) the agricultural sector is not researched homogeneously, there are open niches, which remain unexplored; (2) data collection, maintenance, sharing, interconnection and processing are not sufficiently developed; (3) stakeholders require customisation possibility to fit AI to their farm ecosystem and increase its precision; (4) stakeholders are more interested in decision-support systems than autonomous systems; (5) stakeholders worry about cyberattacks, which can cause destructions through autonomous systems; (6) additionally, they worry about dependency on technology, whose failure can cause losses, while manual maintenance is restricted due to autonomous system exploitation; (7) public data platform required for all agricultural data to be compiled; (8) upgrade of existing farm is restricted by finance, knowledge, experience and worry about security; (9) there is insufficient experience in how to integrate smart solutions into existing decision making system; (10) open systems are required for customisation needs; (11) smart solutions have to be directed to improve working conditions. O'Shaughnessy et al. (2021) discussed information on agricultural resources, challenges for sustainable crop production, frameworks for smart farming solutions and potential positive and negative technological and social aspects comparing the situations in the U.S. and South Korea. O'Shaughnessy et al. (2021) identified the important element of smart farming development: each cultural region and each farm have its policies and business rules, e.g., governance of water is different in each of the fifty states of the U.S. Therefore, the development of data-driven decision-support systems is a rational solution to investigate workflows and regional specifics, which can be gradually automated in the future. In the meantime, the complexity and diversity of ecosystems underline the demand for customisation and open solutions, which can be freely adapted for required workflow. Also, O'Shaughnessy et al. (2021) mentioned challenges caused by COVID-19, which disrupted agricultural distribution systems. That can be generalised in the demand for decision support systems, which can help humans in situations requiring fast decisions or quick changes in the workflow to save business competitiveness. In the 2020/2021 crop year, China was the leading producer of apples worldwide. Jin et al. (2021) indicated barriers to sustainable apple production in China. Considering that China aspires to be a leader in artificial intelligence, the indicated barriers can be equivalent to world-level challenges. Jin et al. (2021) mentioned the synergy of multiple environmental, economic, and social problems which affect the apple production system. Speaking about effective decision-making, Jin et al. (2021) identified similar problems: (1) low adoption of new technologies and practices; (2) limited access to trustworthy information and knowledge; (3) low resilience to climate shocks; (4) the lack of knowledge in orchard management; (5) uncertainty about market access routes; and (6) land fragmentation and limited collaboration among market players. Of course, smart technologies and artificial intelligence received more attention in terms of development, and much knowledge was collected. However, there is a vast knowledge accessibility gap between practice and research. Going back to the six levels of driving automation, smart fruit-growing is somewhere between Level 1, "Assisted Automation", and Level 2, "Partial Automation". IoT monitoring can be an example of assisted automation providing a warning system, but harvesting robots provide partial automation of some fruit-growing activities. Meanwhile, the paradigm of a digital twin can be aspired as the main driver for smart fruit-growing development in the future because it is suitable for a business process management that maps, monitors, and provides geospatial analysis, forecasts, simulates and optimises the workflows of a business. Verdouw et al. (2021) provided a comprehensive analysis of digital twin models, grouping them by control models: (1) imaginary, (2) monitoring, (3) predictive, (4) prescriptive, (5) autonomous, and (6) recollection where the decision-maker is identified as the important element of control model.

The described challenges were grouped into categories: "environment", "technology", "legislation", and "socio-economics" (Appendix II). To visualise the extracted knowledge, the Nadler-Tushman's Congruence Model was applied with category modifications considering PESTLE classification (Fig. 4). This diagram (Fig. 4) depicts the technological gap identified by the authors through the review of existing scientific literature. The keywords were determined using the brainstorming method.

The gap analysis showed that fruit growers are not ready to use fully autonomous systems for fruit growing because they do not trust artificial intelligence and robots. Autonomous systems can be attacked by intruders to cause destruction, or they can simply break down without the possibility of switching to manual control. Meanwhile, the fruit growers are interested in automatic orchard monitoring and AI-based recommendation systems, which can improve decision-making and optimise business processes. Additionally, fruit growers do not have sufficient knowledge required to integrate smart solutions into their native workflows, and the legacy and standards related to autonomous systems are only in the development stage. The independent fine-grained automation of fruit-growing activities and the development of recommendation systems through the digital twin paradigm can structure knowledge about smart solutions and tune the legacy and socio-economic situation for more effective use. Also, the open systems and a customisation possibility are not sufficiently developed to tune smart solutions to local legislation and existing workflows, let alone limited data sharing. Considering the wish of fruit growers, the human–robot collaborative paradigm of Industry 5.0 is well-suitable for them. Currently, the decision-making systems based on the digital twin paradigm are the most suitable development path going to smart fruit-growing based on the human-robot collaborative paradigm of Industry 5.0.

Carrying out a repeated assessment of the situation from November 2022 to April 2023, the keywords "digital twin" AND "smart farming" provided three publications in 2023. Lemphane et al. (2023) presented an article which discusses the smart farming digital twin concept for pasture management based on the artificial intelligence application. Thapa and Horanont (2023) propose the importance of the implementation of digital twin farming platforms to sustain food security based on the involvement of artificial intelligence, the Internet of Things, big data,

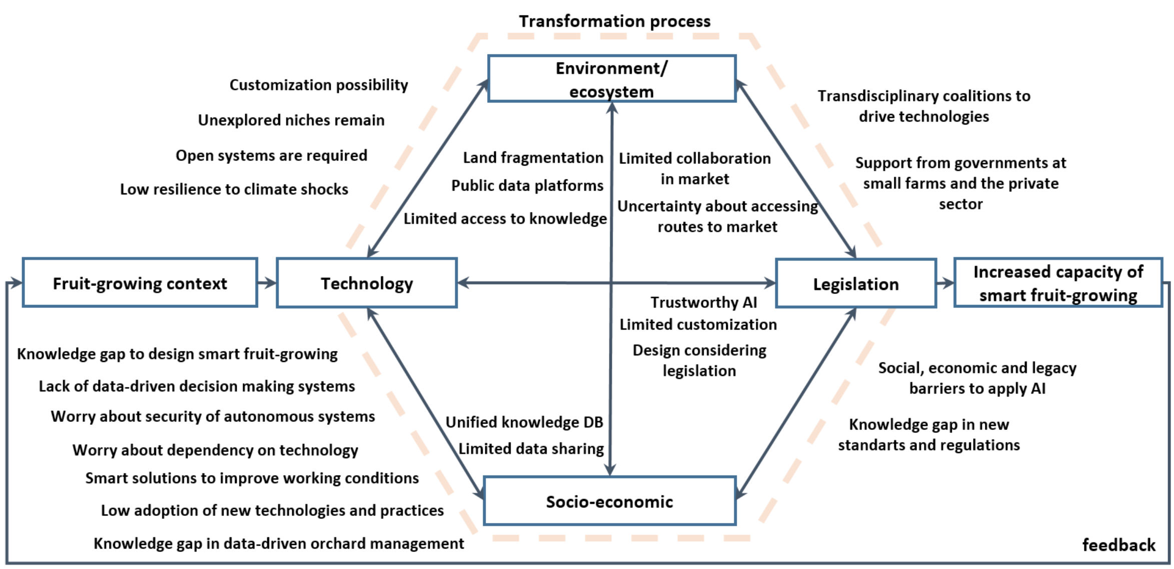


Fig. 4. Challenges or technological gap to increase the capacity of smart fruit-growing

and cloud services to excel in farming using simulation, analysis, and accurate planning for growth in agricultural sectors. Meanwhile, Alves et al. (2023) presented a digital twin of a smart irrigation system composed of an IoT platform and a discrete event simulation model. The articles are not directly related to horticulture; however, they confirm the identified interest of farmers in automatic monitoring, decision-making and AI-based systems and the increase of digital twin trends in the field of smart agriculture.

The authors assume that this study will help the scientific community to plan future studies to optimise research and accelerate the transfer to new smart fruit-growing technologies as it is insufficient to develop an innovation, but it must be done at the appropriate time.

# Conclusions

The amount and quality of developed smart solutions are increasing, and the research information supporting them accumulates in all areas of life, including fruit growing. Using the PRISMA 2020 method for the analysis of published scientific information, the following can be concluded:

- The current level of development of artificial intelligence, automatically controlled devices and decision-making systems limits their direct inclusion in daily fruit-growing practices. The existing achievements indicate the need to improve the structuring of available data, better adapt decision-making systems advice to the needs of the specific fruit-growing farm, environmental and market requirements, and ensure the safety of unmanned aerial vehicle (UAV) applications.
- Closer social and intellectual cooperation between developers of intelligent solutions and their potential end-users should be formed to promote innovative fruit-growing technologies and recognise and substantiate their usefulness.
- The analysis of the existing knowledge indicates the advantages and potential of the digital twin paradigm in developing smart fruit-growing and its future perspectives in creating a dialogue between the field of information technology and practical horticulture.

The study results can optimise research and development of smart fruit-growing technologies.

# Acknowledgement

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## Appendix I

Tab. 2. Keywords describing application and actual research in smart fruit-growing

<table>
<tr><th colspan="2">Vehicles</th><th colspan="2">Satellites</th></tr>
<tr><th>Application</th><th>Research</th><th>Application</th><th>Research</th></tr>
<tr><td>– Object detection for harvesting;<br>– Pest or disease monitoring;<br>– Environment monitoring;<br>– Terrain mapping</td><td>– Automation;<br>– Flight planning</td><td>– Space-based monitoring;<br>– Thematic mapping;<br>– Macro estimation and prediction;<br>– Change and anomaly detection;<br>– Phenology</td><td>– Tuning of AI methods for cultivars and ecosystem</td></tr>
<tr><th colspan="2">IoT</th><th colspan="2">Digital Twins</th></tr>
<tr><th>Application</th><th>Research</th><th>Application</th><th>Research</th></tr>
<tr><td>– Environment monitoring;<br>– Danger prevention</td><td>– Data transmission<br>– increase;<br>– Precision of IoT sensors</td><td>– Autonomous control;<br>– Providing recommendations to humans;<br>– Modeling plant development stages;<br>– Forecasting crop yield</td><td>– Data access safety and security;<br>– Seamless access and data integrity;<br>– Real-time modeling;<br>– Transparency and interoperability</td></tr>
<tr><th colspan="4">Artificial Intelligence</th></tr>
<tr><th colspan="2">Application</th><th colspan="2">Research</th></tr>
<tr><td colspan="2">– Yield estimation and prediction;<br>– Fruit load estimation and prediction;<br>– Object detection for harvesting</td><td colspan="2">– Experimentation with new CNN architectures;<br>– Collection of natural datasets;<br>– Tuning of AI methods for cultivars and an ecosystem;<br>– Design of autonomous vehicle movement;<br>– New algorithms for domain augmentation;<br>– Real-time detection;<br>– Precision of the yield estimation:<br>1) multi-view techniques;<br>2) object tracking application</td></tr>
</table>

# Appendix II

Tab. 3. Keywords describing challenges in smart fruit-growing

| Environment ↔ Legislation | Legislation ↔ Socio-economics |
|---|---|
| – Transdisciplinary coalitions to drive technologies;<br>– Support from governments at small farms and the private sector | – Social, economic and legacy barriers to applying AI;<br>– Knowledge gap in new standards and regulations |
| **Socio-economics ↔ Technology** | **Environment ↔ Socio-economics** |
| – Knowledge gap to design smart fruit-growing;<br>– Lack of data-driven decision-making systems;<br>– Stakeholders worry about cyberattacks, which can cause destruction through autonomous systems;<br>– Stakeholders worry about dependency on technology as their failure can cause losses, while manual maintenance is restricted due to autonomous system exploitation;<br>– Smart solutions have to be directed to improve working conditions;<br>– Low adoption of new technologies and practices;<br>– Lack of knowledge about orchard management | – Unified database or roadmap to link knowledge and innovations;<br>– Data collection, maintenance, sharing, interconnection and processing are not sufficiently developed;<br>– Public data platform required for all agricultural data to be compiled;<br>– Limited access to trustworthy information and knowledge;<br>– Uncertainty about accessing routes to market;<br>– Land fragmentation and limited collaboration among market players |
| **Technology ↔ Environment** | **Technology ↔ Legislation** |
| – Unexplored niches remain;<br>– Customisation possibility to fit AI to farm ecosystem and increase its precision;<br>– Open systems are required for customisation needs;<br>– Low resilience to climate shocks | – Trustworthy AI;<br>– Each cultural region, as well as each farm, has its policies and business rules;<br>– Limited customisation |