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Digital Twins in Agriculture: A State-of-the-art review

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A R T I C L E I N F O

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A B S T R A C T

The Digital Twin enables the distinctions between state sensing, entity understanding and physical automation to be eliminated, through high-fidelity modelling and bi-directional data streams. The concept of real-time virtual representation places the Digital Twin in a unique position to enable digitization in agriculture. The union of data, modelling and what-if simulation can provide an approach to overcome current limitations in decision-making support and automation, across a diverse range of agricultural enterprises. This paper conducts a Systematic Literature Review of Digital Twins in agriculture, identifying current trends and open questions with the goal of increasing awareness and understanding of the Digital Twin and its possibilities.

1. Introduction

The origins of agriculture can be traced back to the early history of human civilisation, remaining one of the world's most important industries even today. The announcement of 4th agricultural revolution or "Agriculture 4.0" in academia and industry has brought the promise of digitization, technological advancement and increased efficiency [1]. While Industry 4.0 has spurred on significant advancements in, and strides towards digitization for manufacturing, medicine and logistics. Benefits of this latest revolution have yet to be fully realized in agriculture, yet digitization is becoming visible as stakeholder leverage new technologies and concepts such as smart farming, precision livestock farming and recently the Digital Twin [2–5]. A Systematic Literature Review (SLR) is conducted, which aims to identify state-of-the-art research on Digital Twins in Agriculture. The main contribution of this work is to provide agricultural stakeholders with a comprehensive overview of Agricultural Digital Twins i.e. state-of-the-art definitions, use-cases, technologies and open questions.

1.1. Digital Twin

The Digital Twin, a real-time synchronized virtual representation of a product, process or environment [6,7]. It provides a novel means to achieve digitization through high-fidelity modelling and simulation [8], with Gartner [9] listing it as a strategic technology for 2019. Manufacturing, Smart cities, Health and Agriculture are just a few areas which are realizing the benefits of adopting the Digital Twin, albeit at differing levels of progress [10]. Matthew Smith [11], in an effort to provide predictions on future technologies, determined that the adoption of Artificial Intelligence (AI) in agriculture will eventually lead to the natural adoption of Digital Twin-like technologies. The steady growth of research on topics such as Cyber-Physical systems (CPS), Internet of Things and AI, coupled with the increasing volume of work on the Digital Twin, gives weight to Smith's reasoning [6].

1.2. Background

The "Digital Twin" (DT) is accredited to Michael Grieve and his work with John Vickers [6,7,12]. The core concepts which would later become the Digital Twin can be traced to a talk on Product-life-cycle management, given in 2002 [6,7]. Being described as a virtual, digital equivalent (representation) of a physical product, and the bi-directional flow of data between them [7]. Table 1 gives an overview of the terminology use to describe the underlying concepts that make up the Digital Twin. The Digital Twin is not strictly a new concept, both industry and research have long worked towards more comprehensive methods for Product Life Management (PLM), however, the Digital Twin provides a unique way to achieve this [7,13].

1.3. Definition

Since its inception and early classification the Digital Twin (DT) has evolved, in terms of requirements, capabilities and applications, growing beyond its original focus on manufacturing [6,7]. Additionally the definition has expanded, in an effort to accommodate and reflect its newfound roles. The Digital Twin's terminology has become

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Table 1
Modelling terminology of a Digital Twin [6].

Digital Twin - Modelling terminology	
PHYSICAL ENTITY	A physical entity can be thought of as a "real-world" entity, its existence is independent of a Digital Twin. The term **"Physical Twin"** can be used when a Digital Twin does exist [6].
VIRTUAL ENTITY	A general model (e.g. un-twinned) or similar domain-specific virtual representation of a product, process or environment.
A **"Virtual Twin"** should be used when a virtual entity is twinned to a physical entity [6].	

increasingly domain-specific, adapting to the context in which it operates [6,7]. Researchers have endeavored to create a general robust definition for the Digital Twin, which remains valid even in the context of newly emerging roles, unforeseen applications and advancements in technology [6,10,14–17]. One such definition provided in CIRP's Encyclopedia of Production Engineering, states: *The Digital Twin is a representation of an active unique "product" which can be a real device, object, machine, service, intangible asset, or a system consisting of a product and its related services* [14]. Looking at state-of-the-art developments and applications of the Digital Twin, David Jones et al. [6] in their systematic review found that current trends, albeit with slight deviations, align closely with the definition provided by CIRP [6,14]. Although this broadening definition has many benefits, a point of growing concern is the inability to accurately distinguish Digital Twins from non-Digital Twins e.g., incorrect labelling of "General computer models" as Digital Twins [6,17]. A further point of ambiguity is the degree of fidelity that must be achieved by a Digital Twin, to be considered an "accurate" representation of the object being modelled [17].

1.4. Classification

A particularly useful metric for constraining the broad scope of the proposed definition, Kritzinger et al. [15] outline a robust classification criterion, based on the data integration level which can be achieved between the physical product and it's virtual representation. As this definition was developed within the field of manufacturing it provides a proxy for assessing the maturity, overlaps and divergences of agricultural Digital Twins against state-of-the-art definitions. In the field of Digital Twin's, three such levels of integration can be distinguished (Fig. 1). The Digital Model (DM), Digital Shadow (DS) and finally the Digital Twin (DT). However, in an effort to avoid confusion, as most papers in the agricultural domain do not differentiate between the three aforementioned Digital Twin types. The integration levels will be re-titled to "subsec:NI", "subsec:PI" and "subsec:FI", see Table 2 [15]. A combination of the CIRP's definition [14] and Kritzinger et al. [15] categorization method provide the bases of the inclusion and classification criteria.

The remainder of the paper is structured as follows, Section 2 introduces the Methodology of the Systematic Literature Review (SLR). Literature identified during the SLR is classified and summarized within thematic applications in Sections 3 and 4 respectivly. Section 5 looks to conceptualize the Digital Twin based on common architectures and technologies identified in literature. The results of the SLR are discussed in Section 6. Finally, the paper concludes in Section 7.

2. Methodology

The Systematic Literature Review (SLR) aims to identify state-of-the-art research on Digital Twins in Agriculture, identifying seminal works, use-cases and open questions. This is done in order to accommodate and promote future work in the area of Agricultural Digital Twins.

2.1. Search Strategy

To identify relevant research the authors consulted online literature data-bases (Table 3), consulting seminal works to identify search terms.

Table 2
The Digital Twin defined by its data integration level [15].

Digital Twin - Data integration levels	
Model (*Digital Model*)	A digital representation without automated data exchange between the entity and virtual model. This is the lowest level of integration which can be achieved. This can be likened to a Digital Twin prototype [7,10,15]. (Fig 1: Left)
Partially-integrated (*Digital Shadow*)	A digital representation with automated information flow in one direction. This information flows for the entity to the virtual representation, meaning a change in the entity is reflected in the virtual representation. This is comparable to a Digital Twin instance [7,15]. (Fig 1: Middle)
Fully-integrated (*Digital Twin*)	A digital representation with automated bi-directional information flow. The Digital Twin like a Digital Shadow has a virtual representation, reflecting any changes in the physical entity's state. The differentiating factor being the Digital Twin can affect the state of the physical entity too, however, the means are dependent on context and entity type [7,15]. (Fig 1: Right)

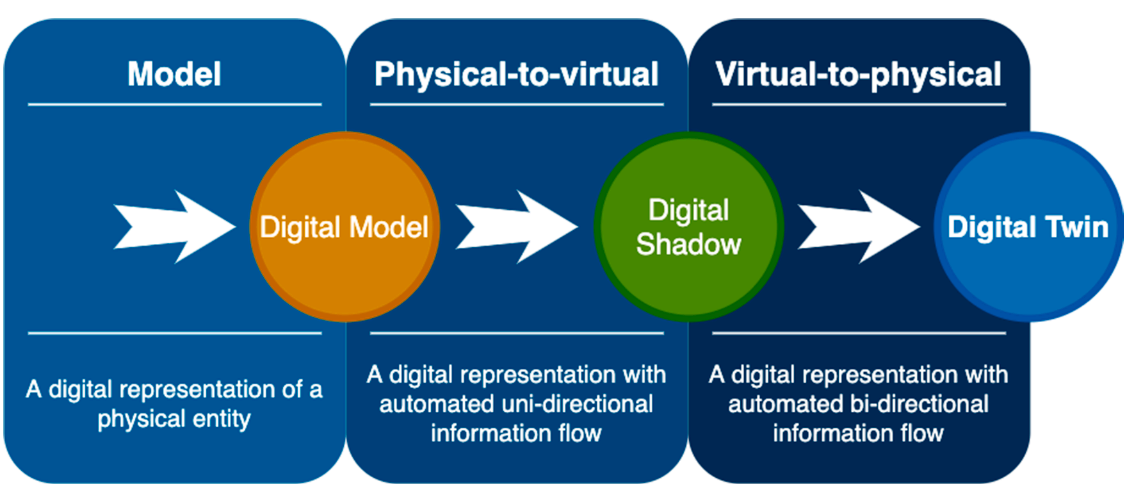

Fig. 1. Digital Twin: Data integration [7,15].

Table 3
Consulted literature databases.

Database	Initial set
1. Google Scholar	1,750
2. IEEE-Explore	8
3. Springer Link	87
4. Scopus	23
5. ScienceDirect	154
6. ACM Digital Library	4
7. Web of Science	15

The review was then conducted using search strings construct based on the information identified during this initial literature search, using the following search string: ”Digital Twin” AND ”Agriculture”. Retrieved literature included journal articles, Research Reports, Research Articles, Book sections, Encyclopedia.

2.2. Selection Criteria and Quality Assessment

Once the documents were collected and the duplicates removed, the papers were filtered to eliminate those that were not directly related to the Digital Twin in Agricultural. Applicable works were identified based on the following characteristics:

1. Articles are: Journal articles, research reports, research articles, conference publications, or scientific encyclopedia.
2. The articles are in English.
3. The primarily focus of the article is on agricultural applications of the Digital Twin.

The vast majority of document retrieved mentioned agriculture in passing or as a use-case for the Digital Twin concepts. As such they are excluded from the final document set.

2.3. Research Questions

These documents were then reviewed with the goal of answering the following research questions (RQs):

RQ1: What is a Digital Twin and how can it be classified?
RQ2: What is the current applications of Digital Twins in agriculture?
RQ3: What is the Digital Twin at a conceptual and technological level?
RQ4: What are the open questions and future research needs?

2.4. Limitations

Accelerator projects and Digital Twins from private industry were excluded, unless they provided sufficient information on implementation, use-cases or technology.

3. Results

The Systematic Literature Review (SLR) culminated in a final corpus of 31 papers, as shown in Table 4. Each item of the corpus is placed within one of four categories, outlined in Table 2 [7,14,15]. The majority of literature identified was not classified as ”subsec:FI”, see Fig. 2 [15]. A primary driver of this was failure to demonstrate, conform-to, or fulfil requirements outlined by the employed definitions, see Table 2. These failures can be partially explained by the early and developing state of research on the topic [5,18–23]. These finding are inline with observations made by Pylianidis et al., that the majority of documented applications in agriculture are still at a conceptual level [5]. As most Digital Twins in agriculture can be view as *in-progress* and as such are not deployed outside of experimental scale or laboratory setting. A major cause which has been attributed to this lagging development is the difficulty and complexity of modelling living entities, with even non-living entities interacting, effecting or effected by living entities [5].

In this regard, data-driven modelling methods, such as machine and deep learning demonstrate a unique ability to capture and model the highly dynamic and complex characteristics of these large multivariate and multi-entity systems (i.e., those containing many interconnected living and non-living entities)[13,24]. Here, the use of IoT connected systems is a key enabler, allowing the collection of direct and indirect measurements (i.e., data) necessary to model the observed system, with the goal of capturing core characteristics of the encompassed entities, environmental conditions and influencing entity-environmental interactions [25]. However, these methods are not without impediment, issues around data and concept drift, along with concerns on the reliability of these methods. Especially in safety and decision critical

Table 4
Literature on Digital Twins in agriculture. **Accessed*, ***Approximately*.

PAPER	CONTENT	INTEGRATION	APPLICATION
VERDOUW-2017 [27]	Review	N/a	Incubators
PYLIANIDIS-2021 [5]	Review	N/a	Agriculture
VERDOUW-2021 [4]	Review	N/a	Smart Farming
NEETHIRAJAN-2021 [28]	Review	N/a	Livestock Farming
LARYUKHIN-2019 [22]	Model description	Model	Farm Management
TAGLIAVINI-2019 [29]	Model description	Model	Fruit Quality
ALVES-2019 [18]	Project description	Partial	Field Irrigation
JAYARAMAN-2016 [21]	Framework description	Partial	Crop Harvesting
NISWAR-2018 [20]	Project description	Partial	Crab Farming
ERDÉLYI-2019 [23]	Model description	Partial	Livestock Farming
LOKE-2018 [19]	Case Study	Partial	Fertilizer Monitoring
SKOBELEV-2020 [30]	Project description	Partial	Wheat Cultivation
JOHANNSEN-2020 [31]	Project description	Partial	Urban Beekeeping
JANS-SINGH-2020 [32]	Project description	Partial	Urban Farming
ANGIN-2020 [33]	Project description	Partial	Crop Cultivation
GHANDAR-2021 [34]	Project description	Partial	Aquaponics
DELGADO-2019 [35]	Platform description	Partial	Farm Management
TSOLAKIS-2019 [36]	Platform description	Partial	Unmanned Ground Vehicles
MACHL-2019 [37]	Model description	Partial	Cultivated Landscape
PARAFOROS-2019 [38]	Platform description	Partial**	Farm Machinery
MOGHADAM-2020 [39]	Project description	Partial**	Orchard Production
HOWARD-2020 [40]	Project description	Full**	Greenhouses
JO-2018 [41]	Project description	Full	Livestock
JO-2019 [42]	Project description	Full	Livestock
KAMPKER-2019 [43]	Business model development	Full	Potato Harvesting
KEATES-2019 [44]	Project description	Full	Livestock/Meat Supply Chain
MONTEIRO-2018 [45]	Implementation Model	Full	Vertical Farming
SMITH-2018 [11]	Forecast	Full	General Farming (Livestock, Crop)
SUSAREV-2019 [46]	Model description	Full	Agricultural Vehicle
AHMED-2019 [47]	Project description	Full	Aquaponics
DOLCI-2017 [48]	Project description	Full	Malt Production

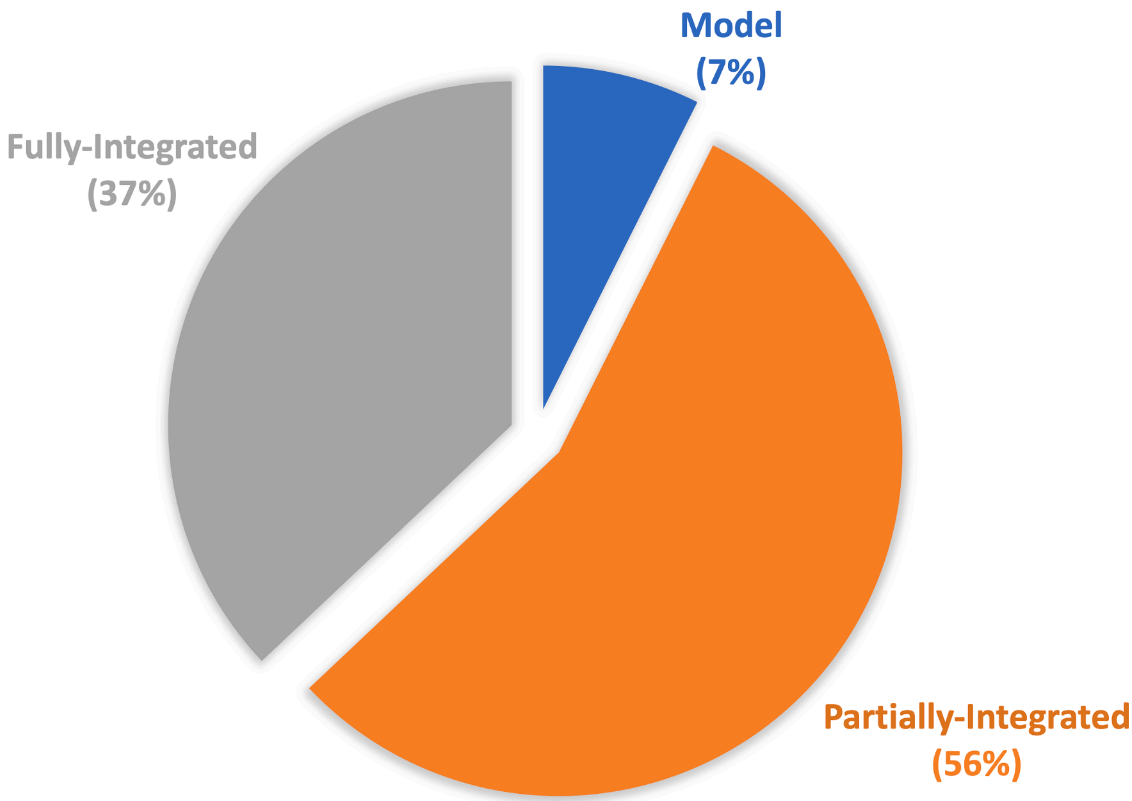

Fig. 2. Paper breakdown by data integration level [7,15].

applications, where anomalous conditions can have adverse effects on the decision making process of such models. If such methods are to gain widespread confidence and adoption in agricultural applications, immediate concerns must be explored and overcome. Hybrid modelling is one such approach that could negate many of current shortcomings experienced by data-driven systems, by restricting the decision making logic based on expert knowledge to ensure reliable and predictable operating behaviour [26]. Although hybrid modelling presents a intriguing route for future application, research on the topic remains limited, with sparse examples of the technology available in agriculture. Therefore, this work highlights data-drive and hybrid modelling approaches as areas of investigation for future research, both in terms of novel applications and exploration of shortcomings and strategies for their mitigation.

The following is a breakdown of literature identified by the SLR, classified by integration level:

3.1. Model

As the smallest grouping with only 2 paper, the lack of examples at the model integration level can be seen as both a positive; applications are falling into higher integration-levels, and a negative; the main reason for this is the limited research on the topic. Tagliavini et al. [29] and Laryukhin et al. [22] provide novel approaches to modelling in the context of Digital Twinning, using multi-physics and multi-agent modelling methods respectively. Although these solutions provide a valuable contribution to modelling entities and their interactions in agriculture, automated data collection infrastructure and methods are key to enabling and adequately reflecting entity state and condition mirroring in real-time. As Digital Twins and digitization is still at an early stage, modelling such agricultural systems can prove challenging and in the case of Digital Twinning is a prerequisite, something which must be accounted for when reviewing agricultural Digital Twins, in this context model development can be understood as an integral step towards a Digital Twin.

3.2. Partially-Integrated

Partially-integrated Digital Twins make up the largest grouping with 15 papers. The reviewed works highlight the difficulty in achieving full integration. However, this stage of development offers an insight into the creation process of Digital Twins when applied to new applications. By allowing stakeholders to gain a deeper understanding of entities, approaches to full integration can be investigated and evaluated [21]. This can be enabled through the collation of data, providing insight into the underlying interactions and behavior of entities. A second method could be to leverage the partially-integrated Digital Twin as a framework for the exploration and testing of new technologies and models, facilitating incremental developments towards a Digital Twin [18–20].

Although the exact degree of automation or required level of direct interaction with the real-world entity is still somewhat ambiguous. The ability to affect the real-world entity is a core requirement set out by the integration definition, necessitating the differentiation between fully and partially integrated Digital Twins, something which is often overlooked in the review literature [19,23,30].

3.3. Fully-Integrated

The review identified 10 papers that documented fully-integrated Digital Twins, achieving the required characteristics of real-time data, sufficiently modelled entity behaviour and feedback mechanisms [40,41,45]. These Digital Twins cover a diverse set of applications including energy optimisation in pigsties, potato harvesters and livestock value chains [42–44]. However, the limited number of papers provides an insight into the new and novel state of the area.

3.4. Uncategorised literature

Although the review identified many insightful applications of the Digital Twin in agriculture, a total of four publications failed to conform to the integration criteria outlined in Table 2. Publications without a clear application (e.g., reviews, concept discussions and domain investigations) were marked as not applicable (i.e., "N/a") to the integration assessment and summarization efforts of this work. However, as a general source of information, these publications proved a valuable resource in contextualising the underlying concepts of the Digital Twin and its development within agriculture, providing vital information and discussion on current and future directions of research for the Digital Twin in agriculture. Therefore, due to there valuable contribution, these publication were included in the resulting SLR corpus.

4. Applications and use-cases

This section looks to assess the core focus of published research in an effort to identify applications and trends of Agricultural Digital Twins. This processes identified a diverse range of applications, with crops found to be the largest area of application with 9 papers, for the full breakdown please see Table 5.

A point of note; Verdouw and Kruize [27] conducted a review on participating start-ups in the SmartAgriFood and Fractals projects. Demonstrating the Digital Twins ability to find commercial success and that the concept is not purely limited to research applications, with a total of six companies identified which utilize the Digital Twin in some capacity [27]. However, as these accelerator projects are not purely research focused, information is somewhat limited (e.g., specific Digital Twin implementations). A lack of detailed information makes determining each projects data integration level extremely difficult. To avoid ambiguity or incorrect results, and better serve the goals of this work, these project will be excluded from the review. The following summarises each paper classified papers within it's thematic cluster.

4.1. Crops; Monitoring, resource optimization and cultivation support

Laryukhin et al. [22] looking to overcome the complexity of agricultural systems, they propose a Cyber-Physical multi-agent approach. These (agent-) entities represent management critical elements (e.g., soil, fertilizer, crop, farmer, etc.) and interact with each other based on finite action and rule sets, within a virtual market [22]. Helping optimize resource use and deployment cost, with the goal encouraging emergent behavior to develop, creating higher fidelity model of the processes and interactions than would otherwise be practical. A key point outlined by Laryukhin et al. [22] is the development of a crop Digital Twin, by monitoring growth and predicting outcomes through simulation.

Skobelev et al. [30] as an extension to [22], propose a multi-agent approach for developing a Digital Twin of wheat, utilizing a comprehensive knowledge base coupled with multi-agent modelling. A novel architecture is outlined which aims to overcoming the limitations of data-driven modelling methods, which can become ineffective at predicting and classifying crop states as the modelled and real-world system diverge. This is especially important in the context of climate change, here the purposed solution utilizes a multi-agent approach to replicate the dynamics of the underlying system, and using the a knowledge base to both detect anomalous states and recommend appropriate measures for correction. This work forms an important step toward climate-resilient decision-support technologies, which are vital for the future success of agriculture.

Table 5
Thematic literature clustering.

Thematic application area	Number
Crops	9
Urban and Controlled Environment Farming	6
Livestock Farming	4
Product Design	4
Supply and Value chains	3
Policy; environment and infrastructure	1

Moghadam et al. [39] discuss an orchard Digital Twin, using 3D LIDAR and cameras a Digital Twin of each tree is created and updated. The goal of this system is to provide real-time condition monitoring and decision support on a large number of trees, while reducing the farmers labour requirements [39].

Machl et al. [37] outline a spatio-temporal Digital Twin of cultivated landscape, in an effort to support geo-design processes for agricultural and rural transport development. Although a detail explanation of data collection methods is not provided, the collection and use of spatio-temporal information is discussed. Implying the Digital Twin maintains an up to date representation of the modeled entity, albeit at a larger time scale that would be seen in other applications.

Angin et al. [33] implemented a farmland Digital Twin for plant monitoring and decision-making support. Outlining a Digital Twin framework using low-powered IoT wireless sensor network based on LoRaWAN and drone imagery. At its core the Digital Twin uses deep-learning to model plants for disease and weeds detection. The work discusses the framework's ability to incorporate new data source and so the modelling and use-case scope could be easily expanded.

Jayaraman et al. [21] explore the benefits of an IoT based data collection system (both spatial and temporal) for observing variations in the state of a physical entity, while under changing conditions (e.g., irrigation, fertilization and crops). A secondary contribution of the work is a review of the Phenonet framework and its application for smart farming.

Loke et al. [19] provide an overview of IoT in India. The case-study put forward shows the relative ease by which IoT and data driven models can be leveraged to create a Digital Twin. The prototype system is part of a larger proposed system for monitoring fertilization and water quality with the goal to minimize water contamination. IoT is shown to be an enabling factor for the future of Digital Twins as is evident in literature [19].

Alves et al. [18] focusing on crop irrigation optimization for yield improvement, put forward an IoT based Digital Twin for monitoring and decision support. The use of multiple data sources is notable, making use of both localized (e.g., sensors on site) and remote sensing (e.g., weather stations) methods, along with a cloud-based architecture for easy integration.

Kampker et al. [43] investigate the creation of a "Digital (twin of a) potato" as a smart service for potato harvesters. The drive for which is to create a method to automatically calibrate a potato harvester. This would allow manufactures and farmers to minimizing any potential damage to the potatoes and ensure optimal calibration of the machine. The system makes use of a sensor equipped artifact, similar in size and weight to a real potato, data from this, coupled with variety information and machine learning, allows the system monitor the artifact and determine the optimal harvester configuration, ensuring correct operation [43].

4.2. Livestock; Monitoring, management and optimization

Erdélyi et al. [23] explore a Digital Twin for pork fatteners, their preliminary results identified issues around modelling systems with uncertain factors, for example human input. As an initial step only singular subsystems and their points of interaction are considered, modelling each through mathematical equations that capture the correlations and characteristics of the production process [23]. Using a combination of production data and animal measurements for simulation, with the goal of optimizing the production process.

Niswar et al. [20] outline an inexpensive IoT based Digital Shadow for real time water quality monitoring in soft-shell crab farming. The system was implementing using MQTT (data broker) and cloud computing for data collection, analysis and decision-making. Testing reveled that each broker (node) can connect up to 25 sensors, allowing the creation of a low-cost high-resolution state monitoring system.

Jo et al. [41] conducted a preliminary investigation into the feasibility of an agricultural Digital Twin. Their work outlines a Digital Twin for the optimal growth of agriculture livestock, achieved through the regulation of barn systems to maintain air quality and temperature within a predefined range. A combination of Big data and model-based simulation are used for identification of scenarios that produce a desirable outcome, which in turn can be used to provide decision-making support and control automation of barn systems. The exact specifications of the model used are not provided; however, a machine or deep learning model is the most likely candidate. To achieve the required state, a combination of fan speed and automated opening of windows needs to be regulated via the barn control systems.

Jo et al. [42] as an extension to [41], focus on a Digital Twin for simulating the energy consumption of a pigsty in order to provide decision support for optimal pigsty design. The proposed Digital Twin uses a combination of IoT data, fan specifications and a model of the operational pigsty. The goal of the Digital Twin is to optimize energy consumption by evaluating and improving the pigsty design to promote optimal air quality, temperature and humidity, with the lowest possible energy input. This is achieved through simulation, allowing the identification of optimal layouts in combination with the correct fan, both in term of power and size. This is done without the need for costly and time-consuming development and testing of real-world infrastructure [42].

4.3. Urban, controlled environment and aquaponic farming

Monteiro et al. [45] discusses the development of a Digital Twin for vertical farming, with a focus on the creation of resilient and adaptable automation for vertical farming structures. The incorporation of redundancy design techniques is proposed, allowing the identification of hardware failures and ensuring that systems fail in a safe manner. To achieve this, a combination of tight integration between the physical and virtual entities during the design stage, system optimization and methods for pre-emptive mitigation of potential risks are used. The primary goal, being the creation of an optimal physical environment for Digital Twinning. This is done in an effort to avoid undesirable behavior in the event of system failure, faulty sensor readings or external factors [45]. Constructing a Digital Twin with these methods can reduced operational interference, which is often encounter in highly dynamic environments (e.g. farm), causing optimal conditions to be extremely difficult to maintain [45].

Ahmed et al. [47] put forward a practical Digital Twin for optimization and management of complex systems. The research provides insight into the benefits of a Digital Twin in the context of aquaponics. Aquaponics is the combination of hydroponics (cultivation in water) and aquaculture (fish farming) in symbiosis. Principal factors impacting such a system include nutrient concentration and water quality, these must be balanced with the cost of operation and output levels [47,49].

The Digital Twin is uniquely suited to the challenges of aquaponics, demonstrated by a small-scale experimental test-bed which utilized a Digital Twin and operated over a four-week period. The combination of real-time data, simulation and automation allowed the Digital Twin to maintain optimal operation by adjusting the core factors of the system. The study evaluated the Digital Twin's internal virtual entity state and simulation output against ground truth data, collected directly by the researchers. They found that pH and dissolved solids were adequately estimated, however, growth rates and nitrate levels were underestimated. They concluded that further integration of real-time data with simulation components would help resolves these issues. This underlines the importance of an accurate representation of the real-world conditions and entity state in order to provide optimal results [49]. Results obtained from this initial research project show a promising avenue for future work, although issues remain regarding management and automation of complex agricultural systems. The implantation of a Digital Twin and results produced provide valuable insight for all domains of agriculture [49].

Ghandar et al. [34] explore an agent model for decision support in urban farming. A Digital Twin of an aquaponic based production system for prediction and decision-making is discussed, implemented using a combination of Internet-of-Thing, machine learning and data driven simulation. The research looks to manage and integrate multiple urban farm within a geographical area, in this case Shenzhen. They found a model based simulation could provide certain benefits over machine learning approaches, especially in low-data situations.

Jans-Singh et al. [32] put forward a Digital Twin of an underground urban farm. The goal of the Digital Twin is to enable remote monitoring, decision-making support, forecasting and optimization, making use of automated and manual data collection methods. Data analysis, data fusion and a dynamic linear model featuring a time-varying provided the best result. However, the need to create bespoke individual system models is pointed out. A notable decision is the use of random forest and multivariate regression algorithms to fill in missing data, something which is not often seen in other Digital Twin applications.

Johannsen et al. [31] propose an agent-based Digital Twin for urban-beekeeping. A combination of sensor data, documentation and agent-based modelling is used to provide remote monitoring and decision-making support. These agents makes use of machine learning, probabilistic, data analysis and data fusion techniques for modelling entities. An interesting consideration of this approach is the use of agents to represent both beehives and beekeepers, among other entities. This is done to identify any impact the beekeeper might have on the beehive, either through direct or indirect action [31].

Howard et al. [40] outline a Digital Twin for general application within commercial greenhouses. Optimization of management and energy consumption are key objectives, requiring the modelling and balancing of multiple interconnected system variables. The Digital Twin is discussed at a high-level and has yet to be implemented. It is described as a Digital Twin for modelling, controlling and optimizing, using Internet-of-Things, agent-based modelling and artificial intelligence.

4.4. Policy, environment and infrastructure

Delgado et al. [35] propose a use-case for a global Digital Twin. The WebGIS framework is introduced, leveraging the spatial-dimension of agriculture, collecting data at the farm/producer level and aggregating it into regional and global views. The proposed Digital Twin could facilitate environmental transparency, allowing policy making to be driven by real-time data open to all stakeholders.

4.5. Product design, smart services and machinery management

Tsolakis et al. [36] present a platform for emulating agricultural machinery in virtual space (*AgROS*). Using cyber-physical interfaces to replicate real-world inputs and environments to better asses system behaviour under real-world field conditions. The physical counterpart can be connected to AgROS, allowing sensor readings to be streamed into real-time, as such the system is described as a foundational step towards an agricultural Digital Twin [36].

Paraforos et al. [38] discuss how pre-existing technology and standards could be used to supplement a Digital Twin. The ISOBUS standard and compatible sensors could allow a field Digital Twin to use farm machinery as a data collection method, this data could including crop yield, temperature and machine state. The expansion and digitisation of such systems follows technology forecast by Matthew Smith [11].

Susarev et al. [46] pursued a Digital Twin application which aligns closely to those commonly found in manufacturing. Their work provides an approach for the creation of a Digital Twin for an unmanned robotic chassis, demonstrating how effective testing is achievable through the use of a Digital Twin. High fidelity models of individual complex structural components are combined to form a comprehensive model of the high-level asset. The ability to test components and their interaction with existing components has proven to be relatively straight forward utilizing their approach, allowing quick evaluation of new component [46].

4.6. Supply and value chain

A Digital Twin for environmental condition management is investigated by R. Dolci [48], utilizing an IOT based Digital Twin to maintain optimal conditions for the production malt [48]. The approach facilitated growth in key quality indicators. A relatively simple Bayesian network trained on a small data-set (one month of data) and Multi-Variate analysis were used to achieve these results.

To improve the cooling and thus the quality of fruit Tagliavini et al. [29] propose a multi-physics modelling and numerical simulation approach as a method to investigate the evolution of fruit quality under varying cooling conditions. The research looked at modelling fruit shape, materials and associated attributes, forming the bases of a future Digital Twin for climate control and quality optimization [29].

A key difference between the Digital Twin presented by R. Dolci [48] and that of Tagliavini et al. [29] are the methods by which the physical entity is virtually represented, with the former using data-driven modelling and the latter using a multi-physics approach.

On the macro level O. Keates [44], outlines a Digital Twin for improving meat and livestock value chains. The Digital Twin is purposed as a method to capture and share key metrics as well as to evaluate their respective performance against a reference model. A key use-case outlined is the generation of missing data through the simulation of the physical supply chain based on the reference model, allowing better understanding of the supply chain. A core goal of this work is to encourage the adoption of IoT technology and the Digital Twin concept by demonstrating the value of its implementation, with a comprehensive road-map to obtain this goal being put forward [44].

5. Topology and technology

In literature the Digital Twin commonly consists of three conceptual elements, see Fig 1 [7,13,15]. A means to observe/ascertain the state of a product, process or the environment in which it operates (Fig. 3). A virtual model, to understand and simulate the effects of state change for a product, process or environment. Finally, a feedback mechanism, used to affect the state of a physical product, process or operational environment. The Systematic Literature Review identified common technologies and methods used to achieve these conceptual elements, the result of which are discussed under the following headings: 5.1 *subsec: P2V*, 5.2 *subsec: modeling* and 5.3 *subsec: v2p* [6,7,13].

5.1. Physical-to-virtual

The Digital Twin utilizes methods and technology to either directly, or indirectly assess and monitor the state of a physical entity in real-time, methods identified during the literature review include:

Remote sensing: This is a diverse topic with a wide range of technologies and use-cases, remote sensing is the science of obtaining information about objects or areas from a distance [50]. The term remote sensing is often linked to the use of drones and satellites in research and can be an invaluable data source [51].

Internet of Things (IoT): In recent years IoT has emerged as a powerful technology, being applied to everything from homes to watches, allowing both the ability to easily and cheaply monitor and control entities remotely. The adoption of IoT in agriculture has incrementally gown in recent years, with many examples of it in literature [2].

Cyber-Physical Systems (CPS): CPS has a strong use-case in Industry and Agriculture. This technology facilitates the integration of both the cyber (Virtual-world) and physical (real-) worlds, using methods similar to those of the Digital Twin (e.g., real-time sensors, feedback mechanisms and dynamic control). Although at a high-level both operate in a similar fashion, their respective focus and core elements do not. The Digital Twin's emphasis on high-fidelity modelling and

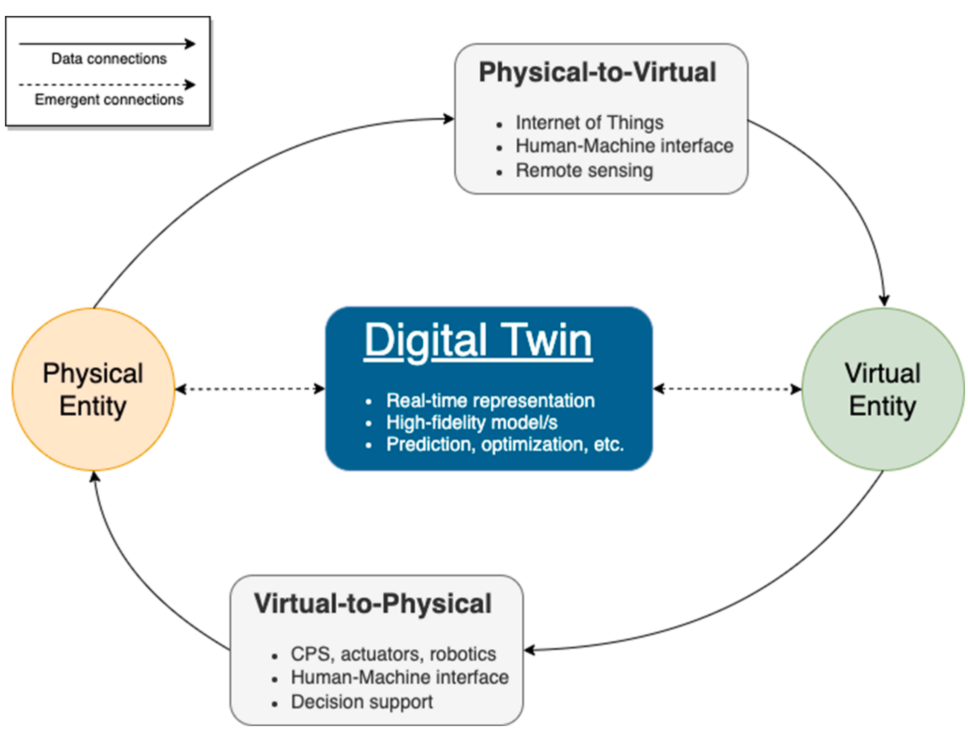

Fig. 3. Digital Twin - Architecture overview [6,7,15].

data, allow it to leverage CPS as a data source, providing insight into the state of an entity [52].

Human-Machine Interface (HMI): As technology has improved and automated tasks typically conducted by humans, greater focus has been placed on the interaction between human and machine. Technologies such as *Augmented reality, Virtual reality, Natural Language Processing, Action recognition, Identity recognition, Gesture control* and *Context aware systems* allow seamless integration of human and machine. This can provide a powerful tool not only for the users of the system, but for the system itself, adding value through efficient and intuitive mechanisms [10,53–55].

5.2. Entity modelling

The quality and fidelity of a model will directly affect the Digital Twin's decision making and simulation capabilities. If done poorly, in the best case it can severely limit the Digital Twin's ability to operate in sub-optimal or anomalous modes. The requirements and tolerances of a model are dependent on the context in which the Digital Twin operates. The primary modelling paradigms utilized for Digital Twinning are *data driven* and *Physics-based* modelling [10].

5.2.1. Data driven modelling

Machine learning and deep-learning algorithms model state and behavior characteristics from entity data [10,56]. The intent to use such methods is widely stated in Agriculture Digital Twin literature, but details on implementation is often limited or absent [11,18,19,41,45]. However, the desire to implement such approaches suggests an ability to overcome limitations of other techniques e.g. cost, time or knowledge [10].

These algorithms are broadly categorized into supervised, unsupervised and reinforcement learning. Supervised and unsupervised algorithms generally require a considerable amount of good quality data to be effective. A solution for data deprived situations is reinforcement learning, which allows an agent to learn from experience and develop optimal policies to maximize its long-term cumulative gains [57]. A major drawback of mathematical model when compared to data-driven approaches is the need for a solid understanding of the entity and its underlying properties. Comparably, data driven models can achieve relatively good result with low effort, even with a relatively small data-set [48].

Despite these algorithms gaining considerable traction in research they suffer from limitations, make them impractical for certain applications. Unsuitability for safety critical applications is often cited, black-box models can have knowledge gaps which are not easily detectable, making their behaviour in complex situations hard to predict [10]. Another issues is that of data and concept drift, which can be exaggerated when modelling entities with evolving life-cycles [10,58]. Digital threads and adaptive frameworks provide a solution to manage and model real-time evolving data, mitigating many challenges encountered when integrating high-dimensional data and disparate systems, however, more research is needed [58,59].

5.2.2. Physics-based modelling

Examples of this approach are primarily found in manufacturing applications. Driven by the need to incorporate real-world phenomenon into virtual representations, mathematically ensuring that behavioural characteristics are accurately modeled, making it a good candidate for safety critical applications [56]. A prerequisite for this approach is that both the entity characteristics (structure, material, etc.) and the effects which act upon it can be directly measured, understood and be mathematically expressed. A downside of this approach is the cost and need for considerable expert knowledge [10].

5.2.3. Combining modelling technique

Although most Digital Twins will utilize either *physics-based* or *data-driven* modelling approaches. A combination of both approaches, or an ensemble of models has been document in literature. The combining of techniques is done to reduce the associated drawbacks of each, leveraging the strengths of each [10,20,26].

5.3. Virtual-to-physical

A Digital Twin must not only monitor and virtually represent an entity's state, but in addition provide a feedback mechanism [15]. Allowing the assertion of a decision-making, optimization or simulation process by influencing an entity, either directly or indirectly. This can be achieved through the adjustment of design, process or environmental parameters [6]. Methods identified during the literature review include:

Cyber-physical systems (CPS): The relatively close conceptual alignment with the Digital Twin and general ubiquity in industry and agriculture makes incorporation extremely attractive. Providing an effectively medium through which a physical entity can be managed [52].

Prediction and Optimization through Simulation: The Digital Twin can leverage what-if simulations to predict and optimize future states, this can be used to reduce cost, optimize operation/management processes and avoid anomalous outcomes. The manifestation of this is highly dependant on the entity type and the context in which it operates, more research is needed [6,10,13,15].

Human-Machine Interface (HMI): Methods can include Augmented reality, Virtual reality, Web and Phone interfaces. The incorporation of a humans into the Virtual-to-physical loop provides a value recourse, simplifying digitization requirements. However, consensus on its use has yet to be reached [6,13,53,60].

6. Discussion

The following is an attempt to summarize the benefits, blocking requirements and open questions identified during the review.

6.1. Benefits for Agriculture

Agriculture is an expansive term, covering everything from tillage to aquaponics, with each area containing its own unique set of challenges and requirements. Agriculture increasingly relies on technology to monitor and understand the multi-scale environments of which it's comprised [4,25,28].

The digitization of process and entity knowledge for both current and new farming methods can be supported by the Digital Twin [4,18,44, 48]. Providing an avenue to achieve the future food production and supply chain efficiencies promised by agriculture 4.0 [45]. The combination of high-fidelity models, what-if simulation, Internet-of-Things and Cyber-physical systems enable the identification and mitigation of internal and external factors impacting entity productivity, health, etc [10,21]. These benefits are broadly summarized in Figure. 4. The European Union's SmartAgriFood and Fractals projects demonstrated that Digital Twins can be practically applied to agricultural use-cases, illustrating the Digital Twin's establishment in industry and value beyond pure research [1,27]. However, many challenges and limitations exist in literature.

6.2. Challenges

Kritzinger et al. [15] proposed the primary definition used to categorize Digital Twin literature. The simple nature, versatility and relative ease of application are ideal attributes for this use-case. However, the ridged "Digital Model", "Digital Shadow" and "Digital Twin" classification thresholds can be limiting in case of agriculture. As intermediate steps have proven to enable, or in some cases be a requirement for the creation of a Digital Twin, especially where complete process

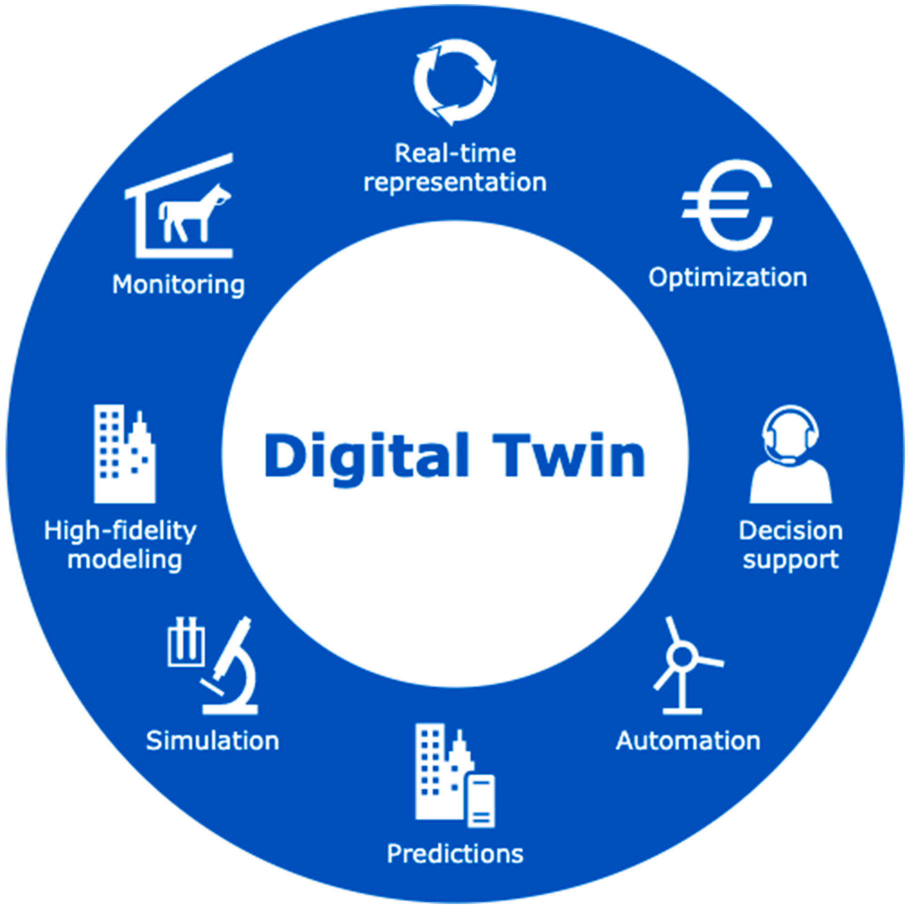

Fig. 4. Digital Twin: Implementation benefits [7,10].

automation is not possible [4,15]. Verdouw et al. [4] based on a literature analysis of Digital Twins and their application in smart farming. Purpose an updated definition that facilitates and reduces the complexity of applying the Digital Twin concept in agriculture, by capture the nuances and dynamic nature of agricultural requirements. Although this definition is a step in the right direction ambiguity still remains. Like, at what point is model fidelity sufficient for a Digital Twin, taking a Digital Twin of a cow as an example; what would an automated bi-directional information flow look like? A crucial challenge for agricultural Digital Twins will be the expansion of current definitions to answer these questions, while obtaining broad agreement in research and industry [4,15,61].

Data privacy and ethical concerns need to be addressed, as collection of sensitive data becomes the norm, the issue of data ownership will become critical in applications where uniquely identifiable information is used [6,10]. Technological and legal solutions can be leveraged to facilitate this, but these concerns need to be addressed directly through training and agreements with and between relevant stakeholders [44].

Data quality and pre-processing is an ongoing issue, without good data models will inevitably under-perform. Improvements in outlier detection, data generation and development of gold standard data-sets are needed [10]. The issues of data and concept drift in data driven models will also need to be managed, requiring the implementation of mechanisms to identify and rectify such anomalies [62]. Methods to reconcile data with significant temporal differences will be required, in-order to take full advantage of available data sources and provide context to entity behaviour at different temporal-scales, something which is critical in agriculture [22,60].

Jo et al. [41] highlight the need for further research on system and data integration, especially in complex systems where processes and entities are not well understood [41,49]. Taking their Digital Twin example, modelling at farm-level would require in-depth inter-disciplinary collaboration and integration of multiple complex system models, something which is limited in current research [3,18,45,56]. As data is limited in many agricultural situations, methods to allow the entity's life cycle to be learned and modeled overtime may need to be developed [62].

6.3. Future work

The review identified no less than 12 papers referencing the use of Internet-of-Things (IoT) technology, demonstrating the technology's growing ubiquity in agriculture [11]. The remaining literature [23,44,46] made use of simulated data, unspecified methods, or empirical (technical) data respectively (Table 4). However, the requirement to collect data in real-time must be fulfil, meaning that continuation of the aforementioned research would most likely result in the application of IoT technology [4,7,14,15]. The development of frameworks, standard, privacy, evaluation methods and software will be crucial to aid the transition to, and implementation of such technology.

Kampker et al. [43] taking a potato harvesting as a use-case, investigate methods to incorporate the Digital Twin into existing products. The solution demonstrates how a business model can be developed to capitalize on the added value of the Digital Twin. Enabling the development of smart services for existing products. An example of this might be the digitization of advanced operational knowledge without fundamentally changing the product offering. This work shows the ability of the Digital Twin to contribute directly to a products monetary value. If the Digital Twin is to be successful, meaning, to gain widespread adoption, research on methods and frameworks for developing and implementing such business models will be mandatory [43].

Experimentation is a crucial tool for informing management practices in agriculture. Digital Twins could be used to overcome current difficulties faced by stakeholders e.g., time and cost. A means to conduct quick iterative experiments based on high-fidelity models could allow stakeholders to gain insight to into known and unknown phenomena in an efficient and timely manner [10]. However, while simulation is often mentioned in the literature, actual implementation of simulations or the required frameworks for agricultural use-cases are extremely limited. Research into approaches and methods for developing and evaluating simulations of agricultural systems will be required to unlock the full potential of the Digital Twin [6,7].

The importance of cross-domain research cannot be understated. However, method need to be developed to capture expert knowledge and integrate it with a Digital Twin [4,10,28]. Other open questions include how model fidelity regarding biological systems can be evaluated and what methods can be leveraged for facilitating Virtual-to-physical interactions between the virtual and Digital Twin [6, 15].

In general more research is need on applying the Digital Twin agricultural, including the identification of new use-cases and experimenting with new approaches on current ones. The use of various machine and deep-learning techniques, or a combination of models from different domains could be an interesting direction for research [3].

7. Conclusion

To conclude, the Digital Twin is a powerful concept that has a promising future in agriculture, with current work covering a range of use-cases including crops, robotics and aquaponics, enabled through technologies including Internet-of-Things, Machine Learning and Cyber-Physical Systems [11]. However, open questions will need to be tackled and answered if the Digital Twin is to be broadly successful in it's adoption across all agricultural use-cases [6].

The volume of research on agricultural Digital Twins remains limited, with a primary focus on investigating and demonstrating the feasibility of applications and use-cases. The literature review identified key areas for future research such as simulation, biological systems modelling and business model development, which are required to allow the growth and adoption of the Digital Twin within agriculture. The development of novel methods, agricultural specific definitions and the implementation of enabling technologies will be necessary to overcome current limitations and challenges [3,4]. The Digital Twin provides an exciting opportunity to enable modelling, simulation and automation of dynamic systems and provides an exciting opportunity to achieve true digitization in complex area such as agriculture.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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