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Artificial intelligence, blockchain and IoT in agribusiness management: Emerging applications, opportunities and challenges

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ABSTRACT

The shift from labour-intensive production methods to sophisticated, autonomous agricultural ecosystems is one of the largest technical revolutions in food and agriculture. Agriculture 1.0 was about human and animal power. Agriculture 2.0 was about mechanization and increased inputs. Agriculture 3.0 was about precision agriculture. Agriculture 4.0 was enabled by connected digital technologies. Agriculture 5.0 is about autonomy, sustainability and human-machine collaboration. AI, IoT and blockchain are seen as complementing technologies for integrated and data-driven farm management systems. Real-time data may be sent via IoT using soil, weather, crop, mechanical and ambient sensors. Machine learning and AI convert these data sets into predictive and prescriptive intelligence for crop monitoring, yield forecasting, disease and pest detection, irrigation scheduling, resource optimization, and risk management. Blockchain can provide distributed, tamper-proof records to improve traceability, transparency, authentication, data integrity, and confidence in the agricultural supply chain. We are studying AI-IoT-blockchain systems where intelligent algorithms analyze sensor data and blockchain based platforms securely record crucial transactions or events. Smart agriculture is analyzed using soil and weather sensors, multispectral and hyperspectral imaging, remote-sensing archives, RFID/NFC tags, historical yield data, soil survey maps, tractor telematics, supply-chain databases, farmer observations, climate predictions and plant-health databases. These technologies are applicable to crop production, precision irrigation, disease diagnosis, smart greenhouse management, supply-chain traceability, certification, agricultural financing and agri-robotics. High deployment and maintenance costs, poor rural connectivity, data quality issues, cybersecurity and privacy issues, blockchain scalability, energy requirements, interoperability, regulatory uncertainty, lack of technical expertise, agricultural data ownership and benefit sharing limit widespread use. To address this, possibilities include low-cost IoT infrastructure, edge computing, energy-efficient systems, federated learning, permissioned and hybrid blockchain architectures, standardized data protocols, capacity development, and supportive institutional and regulatory structures. The analysis concluded that AI, IoT and blockchain might provide a technology base for more efficient, transparent, resilient and sustainable agriculture methods. The way forward will include multidisciplinary cooperation; farmer-centric system design; interoperable digital infrastructure; responsible data governance; and agricultural technology that is both economically and technically accessible.

Keywords: Analysed, Blockchain, Rural, IOT, Agriculture

Introduction

Through evolution, agriculture has been tightly related to technical development, socio-economical change and the shifting needs of food and resource systems (Bhat *et al.*, 2021) [1]. Over the past two centuries agricultural production has shifted from mostly manual and subsistence-based, to more mechanized, data-driven, automated and linked production systems (Commission CA, 2006; Charlebois *et al.*, 2014) [2, 3]. This transition has been brought about by the need to boost productivity, improve the efficiency of use of resources, decrease production risks, handle labor restrictions and react to rising concerns related with climate change, environmental degradation, population expansion and food security (Bosona *et al.*, 2013) [4]. The current move to Agriculture 4.0 and Agriculture 5.0 is a paradigm change in the way agricultural companies produce, process, share and use information to make decisions (Özer *et al.*, 2011) [5]. Agriculture 1.0 is often considered the first stage of agricultural modernization, based mostly on human labour, animal power, traditional knowledge and regionally tailored production strategies (Lu *et al.*, 2017) [6]. Farm management choices were based mostly on farmers' experience, observation, seasonal trends and hereditary expertise. Such systems were frequently well suited to local ecological circumstances, but their productivity was restricted by low levels of automation, poor access to external inputs and heavy reliance on human and animal labor (Lin *et al.*, 2018; Caro *et al.*, 2018) [7, 8]. Thus, the agricultural output was largely dependent on the availability of land, climate variability, availability of labor and efficiency of old production systems (Leng

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et al., 2018) [9]. farm 2.0 was born with the development of farm automation and industrialization. The development of tractors, mechanical harvesters, irrigation systems, better crop varieties, synthetic fertilizers, insecticides and other technology inputs significantly changed agricultural production methods (Surasak *et al.*, 2019) [10]. This transition was especially essential during the Green Revolution. The introduction of high-yielding cultivars, increased irrigation, fertilizer application, crop protection and automation has led to large gains in the productivity of key cereal crops in numerous regions of the globe. During this age, the potential of technological intensification to increase food availability and agricultural production was seen (Mao *et al.*, 2018) [11]. However, the productivity-oriented approach of agricultural intensification created also substantial environmental and resource-related problems. The heavy dependency on external inputs, the overuse or ineffective use of fertilizers and pesticides, the depletion of ground water, soil deterioration, energy consumption and the rising production costs have exposed the limits of a solely input intensive strategy. These issues therefore led to the development of technology to improve the accuracy with which agricultural inputs may be administered (Dey *et al.*, 2021; Tian, 2017; Demestichas *et al.*, 2020) [12, 13, 14]. The late twentieth century saw the birth of Precision Agriculture (PA), a giant step toward Agriculture 3.0. The 1990s saw advances in Global Positioning System (GPS), Geographic Information Systems (GIS), remote sensing, yield monitoring, and variable-rate application technologies that allowed agricultural managers to identify and react to spatial and temporal heterogeneity within fields (Menon *et al.*, 2021) [15]. Precision agriculture established the notion of site-specific management instead of considering a whole field as a homogenous production unit (Tiware, 2020) [16]. GPS technology was used for the precise location of agricultural equipment and field observations and GIS was used to manage and display spatially linked agricultural information (Sharma *et al.*, 2020) [17]. Yield monitors provide information on agricultural production at a location-specific basis, whilst remote sensing technology made it possible to measure crop condition, vegetation features, soil variability and water stress across a greater region. These improvements provided the technical basis for data-supported agricultural management (Fernandez *et al.*, 2020) [18]. Agriculture 4.0 is an additional shift that involves the growing use of technology from the wider Industry 4.0 paradigm in agriculture. Agriculture 4.0, in contrast, is a term used to describe the use of linked systems that can continually create, communicate, process and read agricultural information rather than just stand-alone digital devices (Carter *et al.*, 2008) [19]. The Internet of Things (IoT) has become a key part of this evolution. IoT-enabled agricultural systems include sensors, communication networks, cloud platforms, equipment and analytical systems that generate continuous streams of information from farms and related value-chain processes (Pizzuti *et al.*, 2015) [20]. The IoT sensors may measure soil moisture, temperature, electrical conductivity, pH, nutrient status, humidity, weather conditions, crop microclimates, animal behavior, water availability and equipment performance. The use of high frequency data allows to shift from periodic observation to ongoing surveillance in agricultural decision making. For example, irrigation may be controlled by soil moisture in real-time, rather than predefined cycle times, and environmental sensors might lead to early detection of circumstances that can lead to crop stress or disease development (Lakhani *et al.*, 2017) [21]. However, the value of information created by IoT is primarily dependent on the ability to comprehend massive and complicated data. This has enhanced the role of Artificial Intelligence (AI), machine learning, deep learning and sophisticated analytics in contemporary agriculture management (Mejia *et al.*, 2010) [22]. Artificial intelligence can recognize patterns in agricultural data and allow for applications such as crop disease diagnosis, yield prediction, pest detection, irrigation scheduling, and weather risk analysis, demand forecasting, equipment diagnostics and resource optimization. Agriculture 4.0 is so increasingly defined by the combination of sensing, connection, computing, and intelligent decision making (Bozarth *et al.*, 2008) [23]. Another key element of the digital rev-

olution of agriculture is blockchain technology. Agricultural and food supply chains include many stakeholders including farmers, input suppliers, aggregators, processors, transporters, wholesalers, retailers, financial institutions, regulators and consumers (Aung *et al.*, 2014) [24]. The flow of items and information over these decentralized networks poses difficulties around traceability, transparency, data integrity, authentication and trust (Golan *et al.*, 2004) [25]. blockchain has been offered as a technology solution for producing distributed and tamper-proof records of transactions and product flows (Tian, 2016) [26]. Blockchain, when properly connected with IoT and other digital systems, might possibly link physical agricultural occurrences to verifiable digital records, hence improving traceability and supply-chain accountability (Pass *et al.*, 2017) [27]. The new idea of Agriculture 5.0 takes this digital transition further to higher autonomy, human machine cooperation, sustainability and intelligent automation. Future agricultural systems may be increasingly based on a combination of sophisticated robotics, autonomous equipment, AI-driven drones, edge computing, digital twin, enhanced sensing and next generation communication networks such as 5G and perhaps 6G (Dakshayani *et al.*, 2020) [28]. Agriculture 5.0 does not only automate some agricultural processes, but rather proposes integrated production ecosystems in which robots, biological systems, data platforms, and human decision makers actively interact (Nguyen *et al.*, 2019) [29]. This historical evolution indicates that the development of agricultural technology has been moving from mechanization to precision, connectedness, intelligence, and autonomy. Agriculture 1.0 relied on human and animal labor, Agriculture 2.0 on large-scale mechanization and input intensification, Agriculture 3.0 on spatially informed precision management, Agriculture 4.0 on interconnected digital systems and intelligent analytics, and Agriculture 5.0 on increasingly autonomous, sustainable and human-centred agricultural systems (Haiwu *et al.*, 2018) [30]. So, the combination of AI, IoT and blockchain is not just an acceptance of three separate technologies. Their convergence offers the potential to build an integrated digital architecture for agribusiness management, where IoT generates real-time data, AI transforms data into predictive and prescriptive intelligence, and blockchain provides mechanisms for secure information sharing, traceability, and decentralized trust (Delmolino *et al.*, 2016) [31]. Therefore, the future competitiveness and sustainability of agribusiness may depend not only on technological availability, but also on interoperability, affordability, digital infrastructure, farmers' capabilities, data governance, cybersecurity, institutional support and the development of appropriate regulatory structures (Kosba *et al.*, 2016) [32].

Major scientific contributions

AI and machine learning in agriculture

Machine learning (ML) and AI have quickly become an essential part of contemporary agriculture. Major contributions include the construction of forecasting models for agricultural productivity and resource demands (Bogner *et al.*, 2016) [33]. For example, ensemble methods and neural networks have been trained using past weather and soil data to predict yields with extremely high accuracy. Now computer vision methods (convolutional neural networks) are used to scan drone and satellite pictures to discover illnesses and pests before human scouts can (Gallersdörfer *et al.*, 2021) [34]. In greenhouses, predictive controllers based on ML lowered water use by 19% compared to baseline approaches. Reinforcement learning and "digital twins" of farms are developing tools to optimize complicated irrigation plans and supply systems under unpredictability. This became possible with better processing power, open datasets and enhanced sensors (Hoffman *et al.*, 2012) [35].

IoT and sensor networks

The IoT aids in transforming farmlands into instrumented cyber-physical systems. Here, contributions include scalable sensor networks for environmental monitoring. Initial systems employed basic station sensors, while more recent installations use low-power wireless

(LoRaWAN, Zigbee), and drones / satellites for wide-area sensing. Real-time connection (4G/5G or LPWAN) guarantees the data keeps flowing from field to cloud analytics (Prause *et al.*, 2013) [36]. Architectural frameworks have been proposed. Researcher define a multilayer IoT-blockchain system, where Layer 1 comprises IoT nodes (soil moisture, weather, RFID tags, drones), and the higher layers perform connectivity management, blockchain ledger storage, and analytics. Frameworks normalize deployment and highlight contributions in safe data gathering and remote control of actuators (i.e. automated valves) (Wu, 2018) [37].

Blockchain and decentralized traceability

Blockchain's primary contribution is immutable record-keeping. Research shows that permissioned blockchains (e.g., Hyperledger) or public ledgers may record each transaction or sensor reading throughout the supply chain, providing a tamper-proof audit trail (Nyhuis *et al.*, 2008) [38]. Notable implementations include IBM Food Trust (Walmart, Nestlé) which showcased fast 'farm-to-fork' traceability, cutting traceback times to seconds. Blockchain also supports smart contracts, which are used to automate payments and compliance (e.g. automated fair-pay to coffee producers). Onyeaka *et al.* (2026) have accumulated evidence that blockchain with IoT can secure product provenance and prevent fraud (Schmidt *et al.*, 2015) [39]. The decentralization factor ensures that no single entity owns the data, which improves stakeholder confidence. Contributions have highlighted limitations: high energy consumption and low throughput of typical blockchains, which has spurred research into specialized consensus methods in agriculture (Vangala *et al.*, 2020) [40].

Integrated systems

There is a growing research interest in integrated designs incorporating all three technologies. For instance, SmartOrigin 2.0, a combined IoT-AI-Blockchain system (Sarraguça *et al.*, 2009) [41]. It employs LoRa sensors for soil moisture/temperature/humidity, ML models (ensemble and neural nets) for yield prediction and crop disease detection, and Hyperledger Fabric intelligent contracts to record farm operations in an immutable manner (Schander *et al.*, 2003) [42]. This fusion achieved a forecast accuracy of 91% and a water savings of 24% in an actual case study in a chili field. Other research suggest layered systems where data from smart sensors is fused with distant (satellite) data and supplied to decision engines, while blockchain ensures provenance (Renpenning *et al.*, 2015) [43]. These works represent the Agriculture 4.0 paradigm, where AI-based insights are exploited to control automated IoT actuators (e.g. irrigation on/off) and blockchain guaranties the authenticity of data to all players (Domon *et al.*, 2006) [44].

Technology applications and case studies

AI, IoT, and blockchain have been applied in various domains within agribusiness. We categorize by application type:

- Crop Monitoring and Yield Prediction: ML models use IoT and remote-sensed data for crop monitoring. For example, the classification accuracy of crop kind and health approached 100% using multitemporal NDVI images and specific neural architectures. An ML research using fused IoT data (soil moisture, weather) achieved 94% accuracy in forecasting soil moisture levels and automating irrigation management, with a considerable reduction in water consumption (Coskun, 2016) [45].
- Disease and pest detection computer-vision AI (deep CNNs) looks at photographs of leaves or scans of fields. In one paper, an integrated ML-blockchain system using a transformer-based model achieved 94.94% accuracy in detecting numerous agricultural illnesses, while the blockchain ensured data privacy. ML is being used to teach robotic systems to distinguish weeds from crops for spot weeding and many of these systems are still in prototype (Callejón *et al.*, 2015) [46].

- Resource and irrigation Management: IoT sensor networks and ML support smart irrigation systems. In a greenhouse research, AI controllers reduced fertilizer runoff by 74 percent and achieved 87 percent plant growth accuracy compared to a traditional controller. In a soil-moisture research, predictive algorithms combined with actuators reduced energy expenses by 19% over predictive-only approaches (Kumarathunga, 2020) [47].
- Supply Chain Traceability: Blockchain-IoT systems monitor products from farm to table Case study: The IBM Food Trust network (Walmart, Nestlé, Carrefour) stores data on the farm origin, processing, shipping and timestamps in a shared ledger. It may identify and remove tainted leafy greens in seconds instead of days, increasing food safety (Mirabelli *et al.*, 2020) [48]. Similarly, Starbucks and Farmer Connect launched a blockchain coffee tracing in which each bag is tagged with a QR code that allows customers to track beans back to the farmer to ensure fair remuneration (Torky *et al.*, 2020) [49]. Everledger and VeChain's efforts in the wine sector have used cryptographically-backed provenance data to dramatically reduce the movement of counterfeit wine. In seafood, Provenance's blockchain tracks catches from the chain to the customer, enhancing certification of sustainable fishing and removing mislabelling (Singh *et al.*, 2020) [50].
- Contracting and Finance: Blockchain intelligent contracts automate processes such as crop insurance payments and commodities trades. Pilots (e.g., trigger events from IoT weather sensors to automatically settle an insurance claim) have showed potential to reduce dispute overhead, but are still evolving (Hu *et al.*, 2021) [51].

Table 1. Technology Applications and Case Studies (Hou *et al.*, 2021; Bermejo *et al.*, 2018; Mahoney, 2021; Shahid *et al.*, 2020; Huang *et al.*, 2019; Salah *et al.*, 2019) [52, 53, 54, 55, 56, 57]

Application / Case Study	Description
Food Supply Chain Traceability (IBM Food Trust – Walmart <i>et al.</i>)	Permissioned blockchain network with IoT tagging. Enabled farm-to-store tracebacks in seconds, improving response to contamination.
Coffee Traceability (Starbucks / Farmer Connect)	Blockchain platform with QR codes; consumers trace each coffee batch back to farmers, ensuring fair payment and quality guarantees.
Wine Authentication (Everledger / VeChain)	Blockchain ledger records grape origin and vinting for premium wines; prevents counterfeiting and assures buyers of authenticity.
Seafood Sourcing (Provenance / Sea to Table)	Blockchain/IoT chain-of-custody for fish; tracks catch location and handling, deterring illegal fishing and mislabeling.
Precision Irrigation (LoRa Sensor Network + AI)	SmartOrigin 2.0 system: LoRa sensors measure soil moisture, AI predicts yield/disease and controls irrigation. Achieved 91% yield prediction accuracy and 24% irrigation water reduction.
Organic Produce Certification (Hasan <i>et al.</i> , 2024)	IoT sensors monitor soil, air and crop parameters; blockchain logs compliance with organic/Non-GMO labels. Ensures "mislabel-proof" transparent certification.

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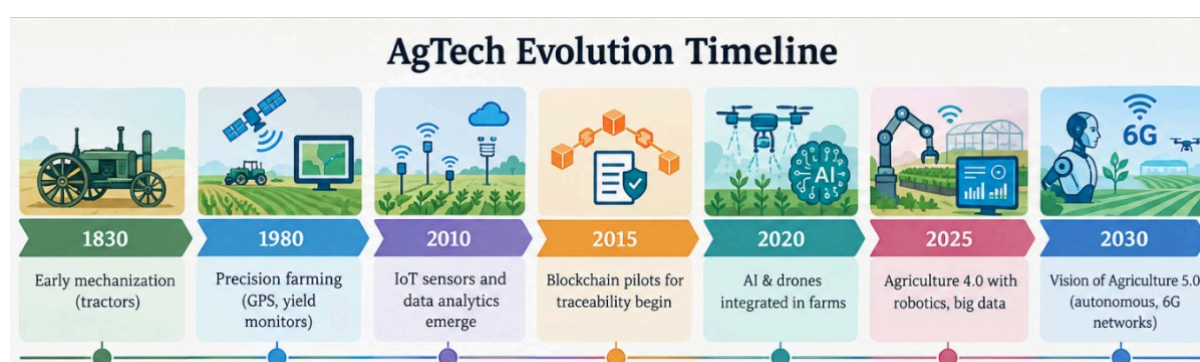
Application / Case Study	Description
Crop Classification (Satellite NDVI + ML)	ML models (e.g. custom TiDE algorithm) classify crop types from medium-resolution NDVI time-series, achieving 100% accuracy without high-res imagery.
Smart Greenhouse Control (ML-Predictive Algorithm)	ML controller in greenhouse uses sensor data to regulate conditions; reported 19% energy savings vs simple prediction model, and 41% vs traditional control.
IoT Soil Moisture Analytics	Study with IoT sensors and edge ML: achieved 94% moisture prediction accuracy, 24% energy reduction; blockchain ensured secure, traceable data.
Smart Auctions / Logistics	(Developing) Auctioning crops via smart contracts, or scheduling shipments, based on tamper-proof IoT quality reports (currently prototypes).

Application / Case Study	Description
Agri-Robotics	(Futuristic) Robot harvesters using deep learning to identify ripe fruits/vegetables and coordinate via IoT; blockchain may record robotic actions for audit (research stage).

Datasets and sensors in smart agriculture

Soil moisture, temperature, pH sensors

Sensors for soil moisture, temperature and pH embedded or directly planted in agricultural fields offer real-time information regarding soil conditions. These sensors monitor key factors that determine the development of crops and the availability of nutrients. The data obtained may be used with artificial intelligence and machine learning algorithms to enhance irrigation timing, fertilizer application and other field management procedures (Davcev *et al.*, 2018) [58].



Weather Station (Rain, Wind, Humidity)

Meteorological stations, fitted with sensors that measure rainfall, wind speed, temperature, and relative humidity, provide localized meteorological information for agricultural decision-making. These data are especially important for estimating agricultural water demands, irrigation needs, and future environmental pressures. Weather data and machine learning algorithms may assist to anticipate crop performance better and help farmers adjust to changing weather conditions (Salihoglu *et al.*, 2018) [59].

NDVI and Multispectral Cameras

NDVI and multispectral cameras are installed on drones, aircrafts or satellites to collect large-scale data on crop health and plant conditions. These imaging devices give spectral information that may be used to derive vegetation indices such as the Normalized Difference Vegetation Index (NDVI). The obtained data are utilized for crop health evaluation, stress detection, crop segmentation, biomass estimate and yield prediction (Waqas *et al.*, 2018) [60].

RFID/NFC Tags

Crates, containers, pallets or individual agricultural items may be fitted with Radio Frequency Identification (RFID) and Near Field Communication (NFC) tags to provide traceability in the supply chain. Data gathered at diverse points like farm, transit system, storage facility and retail point may be connected to blockchain records. This combination may enhance traceability and assist verify origin, transportation, validity and handling history of agricultural goods (Baralla *et al.*, 2019) [61].

IoT Actuators (Valves, Pumps)

IoT-enabled actuators, such as irrigation valves, pumps, and automated control systems, may be remotely or automatically operated by agricultural activities. Artificial intelligence based systems may use

sensor information to decide the time for initiation of irrigation or other field activities. Furthermore, the actuator operation records may be examined to assess the system performance and to enhance the decision making models continually (Dasaklis *et al.*, 2019) [62].

Crop Images (RGB, Hyperspectral)

RRGB and hyperspectral crop photos give useful visual and spectral information for constructing artificial intelligence models for crop monitoring. Such records may be used to detect illnesses, pests, nutritional deficits and other visual or spectral anomalies. For example, picture datasets with wheat rust symptoms may be utilized for training convolutional neural networks and other deep learning models to identify illness automatically (Goldratt *et al.*, 2016; Abolghasemi *et al.*, 2020) [63, 64].

Historical Yield Records

Historical yield records of individual farms, agricultural research stations, government databases or regional agricultural statistics are crucial for predictive modelling. These data are often utilized as target variables in machine learning algorithms to anticipate future crop production. Historical yield data integrated with meteorological, soil, management and remote sensing data may increase the accuracy of yield forecasting systems (Zhou *et al.*, 2007) [65].

Soil Survey Maps

Soil survey maps give spatial information on soil types, fertility, texture, drainage and other soil properties. These maps are usually accessible as geographic information system (GIS) layers and may be interfaced with machine learning and precision agricultural systems. This combination allows for site-specific management such as variable rate application of fertilizers, irrigation, soil amendments and other agricultural inputs (Dong *et al.*, 2019) [66].

Remote Sensing Archives (Sentinel-2, Landsat)

Archives of remote sensing (e.g., Sentinel-2, Landsat) offer a rich set of time series satellite images for monitoring agricultural landscapes. These datasets may be used to create vegetation indices, moisture indicators, temperature information and other environmental factors. Historical satellite data are especially useful for monitoring crops, assessing land use, analyzing drought, classifying crops and developing forecasting models (Hassija *et al.*, 2020; Umamaheswari *et al.*, 2019; Tsang *et al.*, 2019) [67, 68, 69].

On-board Tractor Data (Telematics)

Today, farm equipment produces a wealth of data thanks to GPS, telematics, on-board sensors and machine monitoring devices. Tractor data might consist of location, speed, fuel consumption, implement performance, and operational records. The data may be examined to optimize precision planting, variable rate spraying, field navigation, equipment use, and overall farm operating efficiency (Jiang *et al.*, 2019; Shen *et al.*, 2019) [70, 71].

Supply Chain Databases

Supply chain databases include transaction records, certification information, product movement data, price information, inventory records and other information linked with agricultural commodities. These statistics may be incorporated into blockchain systems to enhance transparency and traceability in the agricultural supply chain. Such information may also be used to assist discover market trends, enhance logistics, track movement of products and make more educated agriculture choices (Ma *et al.*, 2019) [72].

Blockchain Ledger

A blockchain ledger offers a distributed, tamper-proof record of transactions, supply chain events, and other verifiable information. blockchain may hold data on product movement, certification, ownership and information from IoT in agricultural systems. Data hashes and transaction records may also be used for intelligent contracts to have reliable references, so that planned actions may be executed automatically when certain circumstances are satisfied (Novo, 2018) [73].

Crowdsourced Farmer Reports

Crowdsourced farmer reports are developed using mobile apps and digital platforms where farmers voluntarily capture information on field conditions, pest and disease presence, crop progress, weather events and management strategies. These observations give more ground-level information that may supplement sensor and satellite data. When evaluated effectively, data provided by farmers may be utilized to calibrate IoT devices, enhance machine-learning models and fortify early-warning mechanisms (Ding *et al.*, 2019; Zhou *et al.*, 2018) [74, 75].

Tethered Weather Balloons / IoT LoRa

Weather balloons tethered to the ground and Internet of Things (IoT) technology using Long Range (LoRa) connection may provide data collecting and connectivity in agricultural regions. LoRaWAN gateways are very effective for sending sensor data over relatively long distances with minimal power consumption. Such systems may link dispersed agricultural sensors to cloud-based platforms, providing continuous surveillance even in remote places where traditional communication infrastructure is often inadequate (Hammi *et al.*, 2018) [76].

Climate Forecast Models

Climate forecast models provide numerical forecasts of weather and climate variables that may augment field-level data. Information from forecasting systems and organizations like NOAA and ECMWF may include projections of rainfall, temperature, humidity and other meteorological factors. Combining these predictions with farm-level sensor and historical data may enhance short-term agricultural planning,

irrigation scheduling, crop protection choices and risk management (Derhab *et al.*, 2019) [77].

Plant Health Databases

Plant health databases are compilations of information on crop diseases, insect pests, symptoms, diagnostic records and recorded outbreaks. Such databases may include information produced by agricultural professionals, research institutes, extension organizations and field observation. They may be used to train artificial intelligence systems, supporting automated disease and pest diagnosis, outbreak prediction and development of early-warning systems for crop health management (Sharma *et al.*, 2017; Chae *et al.*, 2018) [78, 79].

Improved Traceability and Trust

Blockchain and IoT may establish transparent and traceable agricultural supply chains by documenting critical events from production to the final sale. As IoT devices may automatically create information about temperature, location, handling and transit, blockchain can provide a secure record of these occurrences (Patil *et al.*, 2017) [80]. Consumers may scan QR codes or use other digital interfaces to obtain specified information and verify the origin and handling history of items. These tools may help cut down on fraudulent claims, improve food safety surveillance and speed up the discovery and recall of tainted items (Puthal *et al.*, 2018) [81].

Decision Support, Data-Driven Artificial intelligence systems can sift through the huge, diversified data collected from farms, meteorological stations, satellites, machines, marketplaces and historical records. These datasets may be used to construct predictive models for yield forecasting, weather adaptive planting, pest and disease prediction, irrigation scheduling and market analysis (Muhtasim *et al.*, 2018) [82]. Such decision-support systems may help to better manage risks by helping farmers and agricultural organizations to predict possible issues instead of just reacting after they arise. Shared digital platforms may also promote cooperation among farmers, researchers, insurers, input suppliers, processors and other stakeholders (Ponnappalli *et al.*, 2021) [83].

High Deployment and Maintenance Cost

Initial investment in IoT sensors, communication infrastructure, computer systems, blockchain platforms, and AI-based solutions may be significant. Long-term expenditures may also include maintenance, calibration, software upgrades, connection and replacement of broken equipment. Such costs may pose significant challenges for small and marginal farmers (Li *et al.*, 2020) [84]. The implementation costs may be reduced using low-cost and scalable IoT hardware such as low-cost sensors and low-power wide-area network technologies. Further improvements in accessibility may be made via public-private partnerships, government assistance, cooperative methods and open source platforms. Community-based digital infrastructure may also enable several farms to share technology resources (Zhou *et al.*, 2020) [85].

Scalability of Blockchain

The generation of enormous amounts of agricultural and IoT data may lead to constraints of blockchain systems in terms of transaction speed, storage needs, computing demands and network congestion. These issues are further exacerbated when several farms and supply-chain players are linked to the same network (Schulte *et al.*, 2019) [86]. To boost scalability, permissioned blockchain networks, Layer-2 solutions, sidechains, and directed acyclic graph based techniques might be investigated. Hybrid architectures may also be implemented, where just the necessary transaction information or cryptographic hashes are saved in the blockchain, but big datasets are retained in traditional databases or cloud services (Bhatia, 2020) [87].

Data Privacy and Security

Agricultural digital systems may capture potentially sensitive information on the location of farms, levels of output, usage of inputs, financial transactions, mechanical operations, and management practices. Unauthorized access, cyberattacks, modification of data, or improper distribution of this information might pose threats to farmers and agricultural businesses (Maddikunta *et al.*, 2021) [88]. Data security may be enhanced by using encryption, authentication, access control, anonymization and secure data-storage technologies. Another option is federated learning, in which AI models may be trained on dispersed data without sending the raw datasets to a central site. Proper data protection procedures and adherence to relevant privacy legislation are also key (Reddy *et al.*, 2021) [89].

Data Quality and Availability

AI models are highly dependent on the quality, consistency and availability of training and operating data. Agricultural data may have missing observations, measurement mistakes, inconsistent formats, sensor noise or regional biases. Also, credible farm-level datasets are lacking in many places (Kumar *et al.*, 2021) [90]. Sensor fusion and automated data-validation techniques may be used to detect flaws and enhance data dependability. Data from a variety of sensors, satellites, meteorological stations, farm records and farmer observations may provide a more complete data collection. Government agencies, research institutes and development groups may also help by providing credible agricultural datasets via suitable open-data programs (Bhat *et al.*, 2020) [91].

Interoperability and Standards

Agricultural firms commonly employ gadgets, software platforms, sensors and databases of multiple vendors. The various communication protocols and data formats might create difficulties in sharing information across different systems. The inability to interoperate may lead to increased expenses and technology dependency on certain platforms (Ferrag *et al.*, 2019) [92]. Adoption of common communication protocols such as MQTT and OPC-UA and defined data formats may promote interoperability. Additionally, middleware solutions may be designed to facilitate the translation of information among multiple IoT devices, cloud platforms, AI applications, and blockchain networks. Common standards may facilitate integration of technology from various manufacturers (Awan *et al.*, 2020) [93].

Energy Consumption

IoT networks, computer infrastructure and blockchain systems may be energy-intensive. This is especially difficult in distant agricultural locations where dependable energy may be in restricted supply. Energy-intensive technologies may potentially raise operating expenses and limit the sustainability advantages of digital agriculture (Chinnaiyan *et al.*, 2020) [94]. Energy efficient sensors and communication systems may save power needs. Field sensors using solar and low power IoT devices may be especially beneficial in distant areas of agriculture. At the computational level, energy-efficient consensus techniques and lightweight AI models may cut energy use. Edge computing may further minimize the quantity of data that has to be sent to centralized cloud servers (Liu *et al.*, 2018) [95].

Connectivity in Rural Areas

In many rural areas, a key obstacle to digital agriculture is the lack of reliable internet and telecommunications infrastructure. Poor connection might prohibit the ongoing transmission of sensor information as well as the disruption of cloud-based AI applications and blockchain networks. Minimal power wide area networks like LoRa and NB-IoT allow communication over relatively long distances with minimal energy needs (Konashevych, 2020) [96]. Satellite-based IoT technologies provide alternative solutions for farms that are geographically separated. Store-and-forward techniques also may store data locally on a temporary basis and send it when connection is available. Large scale digital agriculture still needs long-term enhancement of rural telecommunications infrastructure (Pillai *et al.*, 2020) [97].

Complex Integration and Usability

The combination of AI, IoT, blockchain, cloud computing and other digital technologies may produce technically complicated systems. Farmers could find it hard to use sophisticated interfaces especially in areas where basic computer literacy or technical help is scarce (Dietrich *et al.*, 2020) [98]. User-friendly mobile apps and simple dashboards may make these systems more accessible. Modular and plug and play IoT solutions may ease the installation and operation. Practical uptake of digital technology may be further improved via farmer training programs, demonstrations and partnership with agricultural extension agencies (Abdulrazzaq *et al.*, 2018) [99].

Regulatory and Legal Uncertainty

But the fast growth of AI, blockchain, smart contract technology, and digital agriculture platforms has raised regulatory problems around data ownership, electronic transactions, liability, privacy, certification and automated decision-making. Cross-border agricultural supply chains are further complicated by differences across countries (Ogrean, 2018) [100]. Developing clear regulations will need a collaborative effort of policymakers, technology developers, farmers, academics and industry associations. Industry level norms and defined processes would assist develop common techniques for blockchain based traceability, digital certification, intelligent contracts, and agricultural data management (Ilie-Zudor *et al.*, 2015) [101].

Data Ownership and Incentives

Questions of who owns agricultural data and who should profit from its commercial usage are becoming more significant. Farmers may be hesitant to give information if they are not sure how their data will be utilized or whether they would profit from giving it. Transparent data-governance systems should help clarify ownership, access rights, permission and benefit sharing procedures. Incentive schemes, such as subsidies, service discounts, cooperative advantages or other suitable incentives, might motivate farmers to supply high-quality data. It is important to pay special attention to ensuring smallholders are not left behind in digital agricultural ecosystems (Merkert *et al.*, 2015) [102].

Technical Expertise Gap

AI, IoT and Blockchain deployment demands knowledge of data management, sensor functioning, digital platforms, cyber security and applications of agriculture. A lack of qualified workers might hamper the effective deployment and maintenance of sophisticated equipment, especially in remote locations. Capacity-building programs may bridge this gap by training farmers, extension workers, rural entrepreneurs, students and agribusiness experts. "Technical and entrepreneurial skills can be developed using online courses, practical demonstrations, agricultural technology laboratories, innovation programs and agri-hackathons (Awan *et al.*, 2021) [103].

Standards Harmonization

Challenges might arise from incompatibilities in technological standards when various organizations' agricultural technology need to interoperate. Standard harmonization is very crucial for the development of integrated agricultural ecosystems. Membership of the appropriate international and national standards bodies may assist in improving the interoperability of agricultural technology. Common standards for IoT devices, data interchange, robotics, traceability and digital agriculture services may help boost technology adoption and lower integration costs (Casino *et al.*, 2020; Saurabh *et al.*, 2021) [104, 105].

Conclusion

The convergence of AI, blockchain and IoT is driving innovation in farming. Our comprehensive research reveals that AI/ML models greatly enhance agricultural monitoring and decision-making. IoT networks deliver the real-time data and connection required for fine-grained management, and blockchain introduces trust and transpar

ency throughout supply chains. Combined, these technologies may enhance productivity and sustainability, for example by optimizing irrigation, reducing fraud, and allowing new business models (e.g. data marketplaces and automated contracts). But there are huge barriers to overcome to unlock these advantages at scale, including data protection, maintaining dependable networks in rural regions, technological costs and developing standards and ecosystems farmers trust. Future research objectives include building interpretable AI and federated learning for farming, improving lightweight consensus protocols, and constructing modular structures that farmers may embrace progressively. Cross-sectoral cooperation between agronomists, technologists, policymakers and communities will be vital. The data implies that with careful design and supporting legislation, the confluence of AI, IOT and blockchain may lead to more robust, efficient and egalitarian agricultural systems thereby tackling important global concerns of food security and environmental sustainability.

References

- Bhat SA, Huang NF. Big Data and AI Revolution in Precision Agriculture: Survey and Challenges. *IEEE Access*. 2021;9:110209–110222.
- Commission CA. Principles for traceability/Product tracing as a tool within a food inspection and certification system. *CAC/GL*. 2006;60:1–4.
- Charlebois S, Sterling B, Haratifar S, Naing SK. Comparison of global food traceability regulations and requirements. *Compr. Rev. Food Sci. Food Saf.* 2014;13:1104–1123.
- Bosona T, Gebresenbet G. Food traceability as an integral part of logistics management in food and agricultural supply chain. *Food Control*. 2013;33:32–48.
- Özer Ö, Zheng Y, Chen KY. Trust in forecast information sharing. *Manag. Sci.* 2011;57:1111–1137.
- Lu Q, Xu X. Adaptable blockchain-based systems: A case study for product traceability. *IEEE Softw.* 2017;34:21–27.
- Lin J, Shen Z, Zhang A, Chai Y. Blockchain and IoT based food traceability for smart agriculture. In *Proceedings of the 3rd International Conference on Crowd Science and Engineering*, Singapore, 28–31 July 2018. 2018.
- Caro MP, Ali MS, Vecchio M, Giaffreda R. Blockchain-based traceability in Agri-Food supply chain management: A practical implementation. In *Proceedings of the 2018 IoT Vertical and Topical Summit on Agriculture—Tuscany (IOT Tuscany)*, Tuscany, Italy, 8–9 May 2018. 2018.
- Leng K, Bi B, Jing L, Fu HC, Nieuwenhuyse IV. Research on agricultural supply chain system with double chain architecture based on blockchain technology. *Future Gener. Comput. Syst.* 2018;86:641–649.
- Surasak T, Wattanavichian N, Preuksakarn C, Huang SCH. Thai agriculture products traceability system using blockchain and internet of things. *System*. 2019;14:15.
- Mao D, Wang F, Hao C, Li H. Credit evaluation system based on blockchain for multiple stakeholders in the food supply chain. *Int. J. Environ. Res. Public Health*. 2018;15:1627.
- Dey S, Saha S, Singh AK, McDonald-Maier K. FoodSQRBlock: Digitizing Food Production and the Supply Chain with Blockchain and QR Code in the Cloud. *Sustainability*. 2021;13:3486.
- Tian F. A supply chain traceability system for food safety based on HACCP, blockchain & Internet of things. In *Proceedings of the 2017 International Conference on Service Systems and Service Management*, Dalian, China, 16–18 June 2017. 2017.
- Demestichas K, Peppes N, Alexakis T, Adamopoulou E. Blockchain in agriculture traceability systems: A review. *Appl. Sci.* 2020;10:4113.
- Menon S, Jain K. Blockchain Technology for Transparency in Agri-Food Supply Chain: Use Cases, Limitations, and Future Directions. *IEEE Trans. Eng. Manag.* 2021:1–15.
- Tiwari U. Application of Blockchain in Agri-Food Supply Chain. *Br. Int. Exact Sci. J.* 2020;2:574–589.
- Sharma A, Jhamb D, Mittal A. Food Supply Chain Traceability by Using Blockchain Technology. *J. Comput. Theor. Nanosci.* 2020;17:2630–2636.
- Fernandez A, Waghmare A, Tripathi S. Agricultural supply chain using blockchain. In *Proceedings of the International Conference on Intelligent Manufacturing and Automation*, Mumbai, India, 27–28 March 2020; Springer: Berlin/Heidelberg, Germany; 2020.
- Carter CR, Rogers DS. A Framework of Sustainable Supply Chain Management: Moving toward New Theory. *Int. J. Phys. Distrib. Logist. Manag.* 2008;38:360–387.
- Pizzuti T, Mirabelli G. The Global Track&Trace System for food: General framework and functioning principles. *J. Food Eng.* 2015;159:16–35.
- Lakhani KR, Iansiti M. The truth about blockchain. *Harv. Bus. Rev.* 2017;95:119–127.
- Mejia C, McEntire J, Keener K, Muth M, Nganje W, Stinson T, Jensen H. Traceability (product tracing) in food systems: An IFT report submitted to the FDA, volume 2: Cost considerations and implications. *Compr. Rev. Food Sci. Food Saf.* 2010;9:159–175.
- Bozarth CC, Handfield RB, Weiss HJ. *Introduction to Operations and Supply Chain Management*. Pearson Prentice Hall: Upper Saddle River, NJ, USA; 2008.
- Aung MM, Chang YS. Traceability in a food supply chain: Safety and quality perspectives. *Food Control*. 2014;39:172–184.
- Golan EH, Krissoff B, Kuchler F, Calvin L, Nelson K, Price G. Traceability in the US Food Supply: Economic Theory and Industry Studies. *Agricultural Economic Report No. (AER-830)*. United States Department of Agriculture: Washington, DC, USA; 2004:1–56.
- Tian F. An agri-food supply chain traceability system for China based on RFID & blockchain technology. In *Proceedings of the 13th International Conference on Service Systems and Service Management (ICSSSM)*, Kunming, China, 24–26 June 2016. 2016.
- Pass R, Shi E. Fruitchains: A fair blockchain. In *Proceedings of the ACM Symposium on Principles of Distributed Computing*, Washington, DC, USA, 25–27 July 2017. 2017.
- Dakshayini M, Prabhu BB. An effective big data and blockchain (BD-BC) based decision support model for sustainable agriculture system. In *Proceedings of the EAI International Conference on Big Data Innovation for Sustainable Cognitive Computing*, Coimbatore, India, 18–19 December 2020; Springer: Berlin/Heidelberg, Germany; 2020.
- Nguyen T, Das A, Tran L. NEO smart contract for drought-based insurance. In *Proceedings of the 2019 IEEE Canadian Conference of Electrical and Computer Engineering (CCECE)*, Edmonton, AB, Canada, 5–8 May 2019. 2019.
- Haiwu H, An Y, Zehua C. Survey of smart contract technology and application based on blockchain. *J. Comput. Res. Dev.* 2018;55:2452.
- Delmolino K, Arnett M, Kosba A, Miller A, Shi E. Step by step towards creating a safe smart contract: Lessons and insights from a cryptocurrency lab. *Proceedings of the International Conference on Financial Cryptography and Data Security*. Berlin/Heidelberg, Germany: Springer; 2016.
- Kosba A, Miller A, Shi E, Wen Z, Papamanthou C. Hawk: The blockchain model of cryptography and privacy-preserving smart contracts. *Proceedings of the 2016 IEEE Symposium on Security and Privacy (SP)*. 2016.

33. Bogner A, Chanson M, Meeuw A. A Decentralised Sharing App running a Smart Contract on the Ethereum Blockchain. *Proceedings of the 6th International Conference on the Internet of Things. Association for Computing Machinery*. 2016;177-178.
34. Gällersdörfer U, Matthes F. TeSC: TLS/SSL-Certificate Endorsed Smart Contracts. *Proceedings of the 2021 IEEE International Conference on Decentralized Applications and Infrastructures (DAPPS)*. 2021.
35. Hoffman P, Schlyter J. The DNS-Based Authentication of Named Entities (DANE) Transport Layer Security (TLS) Protocol: TLSA; RFC. Marina del Rey, CA, USA; 2012.
36. Prause G, Mendez MM, Garcia-Agreda S. Attitudinal loyalty and trust in entrepreneurship: Building new relationships. *Int. Entrep. Manag. J.* 2013;9:531-540.
37. Wu L. Blockchain Smart Contracts in Megacity Logistics. Master's Thesis. Pennsylvania State University, State College, PA, USA; 2018.
38. Nyhuis P, Wiendahl HP. *Fundamentals of Production Logistics: Theory, Tools and Applications*. Berlin, Germany: Springer Science & Business Media; 2008.
39. Schmidt M, Münzberg B, Nyhuis P. Determining lot sizes in production areas—exact calculations versus research based estimation. *Procedia CIRP*. 2015;28:143-148.
40. Vangala A, Das AK, Kumar N, Alazab M. Smart secure sensing for IoT-based agriculture: Blockchain perspective. *IEEE Sens. J.* 2020;21:17591-17607.
41. Sarraguça MC, Paulo A, Alves MM, Dias AM, Lopes JA, Ferreira EC. Quantitative monitoring of an activated sludge reactor using on-line UV-visible and near-infrared spectroscopy. *Anal. Bioanal. Chem.* 2009;395:1159-1166.
42. Schander C, Kenneth HM. DNA, PCR and formalinized animal tissue—A short review and protocols. *Org. Divers. Evol.* 2003;3:195-205.
43. Renpenning J, Hitzfeld KL, Gilevska T, Nijenhuis I, Gehre M, Richnow HH. Development and validation of an universal interface for compound-specific stable isotope analysis of chlorine ($^{37}\text{Cl}/^{35}\text{Cl}$) by GC-high-temperature conversion (HTC)-MS/IRMS. *Anal. Chem.* 2015;87:2832-2839.
44. Domon B, Aebersold R. Mass spectrometry and protein analysis. *Science*. 2006;312:212-217.
45. Coskun O. *Separation techniques: Chromatography*. N. Clin. Istanbul. 2016;3:156.
46. Callejón RM, Rodríguez-Naranjo MI, Ubeda C, Hornedo-Ortega R, García-Parrilla MC, Troncoso AM. Reported foodborne outbreaks due to fresh produce in the United States and European Union: Trends and causes. *Foodborne Pathog. Dis.* 2015;12:32-38.
47. Kumarathunga M. Improving Farmers' Participation in Agri Supply Chains with Blockchain and Smart Contracts. In *Proceedings of the Seventh International Conference on Software Defined Systems (SDS)*, Paris, France; 2020.
48. Mirabelli G, Solina V. Blockchain and agricultural supply chains traceability: Research trends and future challenges. *Procedia Manuf.* 2020;42:414-421.
49. Torky M, Hassanein AE. Integrating blockchain and the internet of things in precision agriculture: Analysis, opportunities, and challenges. *Comput. Electron. Agric.* 2020;178:105476.
50. Singh P, Singh N. Blockchain With IoT and AI: A Review of Agriculture and Healthcare. *Int. J. Appl. Evol. Comput.* 2020;11:13-27.
51. Hu S, Huang S, Huang J, Su J. Blockchain and edge computing technology enabling organic agricultural supply chain: A framework solution to trust crisis. *Comput. Ind. Eng.* 2021;153:107079.
52. Hou L, Liao R, Luo Q. IoT and Blockchain-Based Smart Agri-food Supply Chains. In *Handbook of Smart Cities*. Cham, Switzerland: Springer; 2021. Volume 1:1109-1130.
53. Bermejo F, Aguas M, Chaparro M, Domènech E, Echarri A, García-Planella E, Guerra I, Gisbert JP, López-Sanromán A. Recommendations of the Spanish Working Group on Crohn's Disease and Ulcerative Colitis (GETECCU) on the use of thiopurines in inflammatory bowel disease. *Gastroenterol. Hepatol. (Engl. Ed.)*. 2018;41:205-221.
54. Mahoney D. Safety of fresh produce—Should consumers worry? *Food Aust.* 2021;73:28-31.
55. Shahid A, Almogren A, Javaid N, Al-Zahrani FA, Zuair M, Alam M. Blockchain-based agri-food supply chain: A complete solution. *IEEE Access*. 2020;8:69230-69243.
56. Huang H, Zhou X, Liu J. Food supply chain traceability scheme based on blockchain and EPC technology. In *Proceedings of the International Conference on Smart Blockchain*, Birmingham, UK. Berlin/Heidelberg, Germany: Springer; 2019.
57. Salah K, Nizamuddin N, Jayaraman R, Omar M. Blockchain-based soybean traceability in agricultural supply chain. *IEEE Access*. 2019;7:73295-73305.
58. Davcev D, Carbone A, Mitreski K, Kocarev L, Stankovski V. Blockchain-based distributed cloud/fog platform for IoT supply chain management. In *Proceedings of the Eighth International Conference on Advances in Computing, Electronics and Electrical Technology (CEET)*, Kuala Lumpur, Malaysia; 2018.
59. Salihoglu G, Salihoglu NK, Ucaroglu S, Banar M. Food loss and waste management in Turkey. *Bioresour. Technol.* 2018;248:88-99.
60. Waqas M, Nizami AS, Aburizaiza AS, Barakat MA, Rashid MI, Ismail IMI. Optimizing the process of food waste compost and valorizing its applications: A case study of Saudi Arabia. *J. Clean. Prod.* 2018;176:426-438.
61. Baralla G, Pinna A, Corrias G. Ensure traceability in European food supply chain by using a blockchain system. In *Proceedings of the 2019 IEEE/ACM 2nd International Workshop on Emerging Trends in Software Engineering for Blockchain (WETSEB)*, Montreal, QC, Canada, 27 May 2019. 2019.
62. Dasaklis T, Casino F. Improving vendor-managed inventory strategy based on Internet of Things (IoT) applications and blockchain technology. In *Proceedings of the 2019 IEEE International Conference on Blockchain and Cryptocurrency (ICBC)*, Seoul, Korea, 14-17 May 2019. 2019.
63. Goldratt EM, Cox J. *The Goal: A Process of Ongoing Improvement*. Abingdon, UK: Routledge; 2016.
64. Abolghasemi M, Beh E, Tarr G, Gerlach R. Demand forecasting in supply chain: The impact of demand volatility in the presence of promotion. *Comput. Ind. Eng.* 2020;142:106380.
65. Zhou H, Benton W Jr. Supply chain practice and information sharing. *J. Oper. Manag.* 2007;25:1348-1365.
66. Dong X, Zheng X, Lu X, Lin X. A traceability method based on blockchain and internet of things. In *Proceedings of the 2019 IEEE Intl Conf on Parallel & Distributed Processing with Applications, Big Data & Cloud Computing, Sustainable Computing & Communications, Social Computing & Networking (ISPA/BDCloud/SocialCom/SustainCom)*, Xiamen, China, 16-18 December 2019. 2019.
67. Hassija V, Chamola V, Gupta V, Jain S, Guizani N. A survey on supply chain security: Application areas, security threats, and solution architectures. *IEEE Internet Things J.* 2020;8:6222-6246.
68. Umamaheswari S, Sreeram S, Kritika N, Prasanth D. Biot: Blockchain based IoT for agriculture. In *Proceedings of the 2019 11th International Conference on Advanced Computing (ICoAC)*, Chennai, India, 18-20 December 2019. 2019.
69. Tsang YP, Choy K, Wu CH, Ho GTS, Lam H. Blockchain-driven IoT for food traceability with an integrated consensus mechanism. *IEEE Access*. 2019;7:129000-129017.

70. Jiang W, Li H, Xu G, Wen M, Dong G, Lin X. PTAS: Privacy-preserving thin-client authentication scheme in blockchain-based PKI. *Future Gener. Comput. Syst.* 2019;96:185–195.
71. Shen M, Tang X, Zhu L, Du X. Privacy-preserving support vector machine training over blockchain-based encrypted IoT data in smart cities. *IEEE Internet Things J.* 2019;6:7702–7712.
72. Ma M, Shi G, Li F. Privacy-oriented blockchain-based distributed key management architecture for hierarchical access control in the IoT scenario. *IEEE Access.* 2019;7:34045–34059.
73. Novo O. Blockchain meets IoT: An architecture for scalable access management in IoT. *IEEE Internet Things J.* 2018;5:1184–1195.
74. Ding S, Cao J, Li C, Fan K. A novel attribute-based access control scheme using blockchain for IoT. *IEEE Access.* 2019;7:38431–38441.
75. Zhou L, Wang L, Lv P, Sun Y. Beekeeper: A blockchain-based iot system with secure storage and homomorphic computation. *IEEE Access.* 2018;6:43472–43488.
76. Hammi MT, Hammi B, Bellot P, Serhrouchni A. Bubbles of Trust: A decentralized blockchain-based authentication system for IoT. *Comput. Secur.* 2018;78:126–142.
77. Derhab A, Guerroumi M, Gumaï A, Maglaras L, Ferrag MA, Mukherjee M, Khan FA. Blockchain and random subspace learning-based IDS for SDN-enabled industrial IoT security. *Sensors.* 2019;19:3119.
78. Sharma PK, Singh S, Jeong YS, Park JH. Distblocknet: A distributed blockchains-based secure sdn architecture for iot networks. *IEEE Commun. Mag.* 2017;55:78–85.
79. Chae CJ, Cho HJ. Enhanced secure device authentication algorithm in P2P-based smart farm system. *Peer Peer Netw. Appl.* 2018;11:1230–1239.
80. Patil AS, Tama BA, Park Y, Rhee KH. A Framework for Blockchain Based Secure Smart Green House Farming. In *Advances in Computer Science and Ubiquitous Computing.* Berlin/Heidelberg, Germany: Springer; 2017:1162–1167.
81. Puthal D, Malik NS, Mohanty SP, Kougianos E. Everything you wanted to know about the blockchain: Its promise, components, processes, and problems. *IEEE Consum. Electron. Mag.* 2018;7:6–14.
82. Muhtasim MA, Fariha SR, Rashid R, Islam N. Secure data transaction and data analysis of IOT devices using blockchain. In *Proceedings of the 2018 International Conference on Circuits and Systems in Digital Enterprise Technology (ICCSDET), Kottayam, India; 2018.*
83. Ponnappalli S, Shah A, Banerjee S. RainBlock: Faster Transaction Processing in Public Blockchains. In *Proceedings of the 2021 (USENIX) Annual Technical Conference ((USENIX)(ATC) 21), Santa Clara, CA, USA; 2021.*
84. Li S, Yu M, Yang CH, Avestimehr AS, Kannan S, Viswanath P. Polyshard: Coded sharding achieves linearly scaling efficiency and security simultaneously. *IEEE Trans. Inf. Forensics Secur.* 2020;16:249–261.
85. Zhou Q, Huang H, Zheng Z. Solutions to scalability of blockchain: A survey. *IEEE Access.* 2020;8:16440–16455.
86. Schulte S, Sigwart M, Frauenthaler P, Borkowski M. Towards blockchain interoperability. In *Proceedings of the International Conference on Business Process Management, Vienna, Austria.* Berlin/Heidelberg, Germany: Springer; 2019.
87. Bhatia R. Interoperability solutions for blockchain. In *Proceedings of the 2020 International Conference on Smart Technologies in Computing, Electrical and Electronics (ICSTCEE), Bengaluru, India; 2020.*
88. Maddikunta PKR, Pham QV, Prabadevi B, Deepa N, Dev K, Gadekallu TR, Ruby R, Liyanage M. Industry 5.0: A survey on enabling technologies and potential applications. *J. Ind. Inf. Integr.* 2021;26:100257.
89. Reddy PK, Hakak S, Alazab M, Bhattachatya S. Unmanned Aerial Vehicles in Smart Agriculture: Applications, Requirements, and Challenges. *IEEE Sens. J.* 2021;21:17608–17619.
90. Kumar R, Kumar P, Tripathi R, Gupta GP, Gadekallu TR, Srivastava G. Sp2f: A secured privacy-preserving framework for smart agricultural unmanned aerial vehicles. *Comput. Netw.* 2021;187:107819.
91. Bhat SA, Sofi IB, Chi CY. Edge Computing and Its Convergence With Blockchain in 5G and Beyond: Security, Challenges, and Opportunities. *IEEE Access.* 2020;8:205340–205373.
92. Ferrag MA, Maglaras L, Janicke H. Blockchain and Its Role in the Internet of Things. *Strategic Innovative Marketing and Tourism.* Berlin/Heidelberg, Germany: Springer; 2019:1029–1038.
93. Awan SH, Ahmed S, Nawaz A, Maghddid S, Zaman K, Ali MY, Khan Z, Saeed S. BlockChain with IoT, an emergent routing scheme for smart agriculture. *Int. J. Adv. Comput. Sci. Appl.* 2020;11:420–429.
94. Chinnaiyan R, Balachandar S. Reliable administration framework of drones and IoT sensors in agriculture farmstead using blockchain and smart contracts. *Proceedings of the 2020 2nd International Conference on Big Data Engineering and Technology.* Singapore; 2020.
95. Liu X, Chen R, Chen YW, Yuan SM. Off-chain data fetching architecture for ethereum smart contract. *Proceedings of the 2018 International Conference on Cloud Computing, Big Data and Blockchain (ICCBDB).* Fuzhou, China; 2018.
96. Konashevych O. Cross-blockchain protocol for public registries. *Int. J. Web Inf. Syst.* 2020;16:571–610.
97. Pillai B, Biswas K, Muthukkumarasamy V. Cross-chain interoperability among blockchain-based systems using transactions. *Knowl. Eng. Rev.* 2020;35:1–17.
98. Dietrich F, Turgut A, Palm D, Louw L. Smart contract-based blockchain solution to reduce supply chain risks. *Proceedings of the IFIP International Conference on Advances in Production Management Systems.* Berlin/Heidelberg, Germany: Springer; 2020.
99. Abdulrazzaq M, Wei Y. Industrial Control System (ICS) Network Asset Identification and Risk Management. Master's Thesis. Halmstad, Sweden: School of Information Technology, Halmstad University; 2018.
100. Ogrea C. Relevance of big data for business and management. *Exploratory insights (Part I).* *Stud. Bus. Econ.* 2018;13:153–163.
101. Ilie-Zudor E, Ekárt A, Kemeny Z, Buckingham C, Welch P, Monostori L. Advanced predictive-analysis-based decision support for collaborative logistics networks. *Supply Chain Manag.* *Int. J.* 2015;20:369–388.
102. Merkert J, Mueller M, Hubl M. A Survey of the Application of Machine Learning in Decision Support Systems. *Proceedings of the 23rd European Conference on Information Systems (ECIS 2015).* Münster, Germany; 2015.
103. Awan S, Ahmed S, Ullah F, Nawaz A, Khan A, Uddin MI, Alosaimi W, Alyami H. IoT with BlockChain: A Futuristic Approach in Agriculture and Food Supply Chain. *Wirel. Commun. Mob. Comput.* 2021;2021:5580179.
104. Casino F, Kanakaris V, Dasaklis T, Moschuris S, Stachtariis S, Pagoni M, Rachaniotis N. Blockchain-based food supply chain traceability: A case study in the dairy sector. *Int. J. Prod. Res.* 2020;59:1–13.

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- . Saurabh S, Dey K. Blockchain technology adoption, architecture, and sustainable agri-food supply chains. *J. Clean. Prod.* 2021;284:124731.

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