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# Food Safety Related Data Analytics, Digital, and Artificial Intelligence Needs and Opportunities in Controlled Environment Agriculture

## ABSTRACT

Controlled Environment Agriculture (CEA) is increasingly used to grow food (namely fruits and vegetables) in controlled indoor conditions. While often billed as "eliminating" the classical food safety concerns associated with open field cultivation of produce, traditional as well as potentially novel microbial food safety risks are a concern for CEA, as supported by a recent salmonellosis outbreak in the U.S. linked to CEA grown produce. In addition, the use of diverse technologies and practices in CEA represents a challenge in efforts to develop food safety guidance. CEA, particularly precision vertical farms, however, have the distinct advantage of being "data intense" and typically have a better data collection and management structure than is found in traditional agriculture. This may position at least part of the industry to use digital tools digital tools and Artificial Intelligence (AI) to manage manage food safety. Possible AI approaches may include adaptive sampling and interventions depending on the presence of risk factors that could be predicted with the routine data generated during CEA operations. This article summarizes challenges and opportunities for using AI and digital approaches to assure microbial food safety and manage food safety related business risks in CEA.

## OVERVIEW OF CEA

Controlled Environment Agriculture (CEA) is a rapidly growing sector *(79)* due to its use of agricultural techniques to create specific and precisely controlled environments directed towards efficient plant production using limited inputs *(6, 23)*. CEA encompasses a wide array of technologies ranging from "low tech" traditional greenhouses to advanced and more automated soilless "high tech" and closed loop vertical farms. Currently, CEA production largely focuses on specialty crops (e.g., leafy greens, herbs, microgreens, tomatoes), but the term CEA can also include indoor production of mushrooms, fish, and even insects *(17, 23, 34)*. CEA is most commonly divided into soilless growing methods (such as hydroponics) and traditional growing methods (utilizing pots with soil) *(35)*. Both formats use various inputs, including growing media, lighting systems, and structural systems *(55)*. Most CEA systems are characterized by a wide array

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of high-tech operations which include common activities linked to the production of fruit, vegetable and herbs (FVHs) (e.g., seeding, irrigation, harvesting). An increasing number of CEA facilities also include processing and packaging operations. Operations such as cutting, washing and packing, which were usually performed in fresh-cut processing plants, thus are now performed within the CEA facilities, in the same room or adjoining rooms where the crops are grown *(37)*.

Hydroponics is the technique of growing plants using a water-based nutrient solution and can include an aggregate substrate or growing media such as vermiculite, coconut coir, perlite or peat moss *(46, 54, 56)*. Hydroponics differ from traditional soil cultivation methods in that the water is the primary nutrient carrier as opposed to soil; the structural support is offered through the aforementioned substrate or growing media instead of soil. The most common types of FVH commodities cultivated under soilless practices are tomatoes, peppers, lettuce, and other leafy greens, including microgreens. Hydroponics include many different types of cultivation systems such as deep-water culture hydroponics, aeroponics, and aquaponics *(71)*. Deep-water culture is where seedlings are planted into floating rafts so that the roots are immersed in deep, recirculating nutrient rich "ponds." In aeroponics, the roots of the plants are suspended in the air, and water and nutrients are supplied to the plant through a fine mist activated by a timer. Indoor aquaponic systems combine plant production with fish cultivation, using treated water from the fish tanks as a source of irrigation water to grow plants *(51)*. While hydroponics is inherently different from soil-based methods, the overall primary inputs for both methods, which are all relevant to food safety, remain generally similar. These primary inputs include plant seeds, water, nutrients/fertilizers, soil (for traditional methods) and substrates (for soilless methods) *(18)*. Other food safety relevant factors in CEA production include lighting, structural systems and climatic factors (e.g., oxygen, humidity, and carbon dioxide levels) *(18, 38)*.

Lighting systems involved in CEA cover a wide range. Traditional methods utilize sunlight, as commonly seen in greenhouses *(10)*. On the other end of the spectrum are vertical farms where layers of crops are stacked on top of one another, each layer with its own set of lights (typically light emitting diodes [LEDs]) on the bottom of the above structure *(23)*. This allows for precise dosing of lights, and often very defined amounts of red, blue and white light are utilized to increase plant production *(42)*.

Finally, there can be numerous combinations between light and cultivation systems, each combination affecting the structure within the greenhouse/farm. Both hydroponics and traditional soil-based cultivation can be applied into a flat, one tier system using sunlight *(36)*. Hydroponics can also be applied into a multi-level vertical farm using synthetic lights *(23)*. It is unlikely that traditional soil methods will be combined with vertical farming as the weight of the soil poses a challenge for the structure to support. Two commonly seen types of CEA facilities are high tech vertical hydroponic farms utilizing LED lights and middle to low tech hydroponic horizontal farms utilizing sunlight. The latter system, which includes a hydroponic system, with several automated stages of the whole process (e.g., transport of trays/beds from the seeding room to the greenhouse and from the greenhouse to the harvest area), is becoming increasingly popular *(37)*. While this lower tech version may not have full climatic control, it might reduce the initial investment, making it attractive for firms *(36)*.

The range of practices in which environmental factors such as temperature, light, humidity, oxygen, and carbon dioxide are controlled can often be tied with the maturity of the data collection infrastructure. On one end of the spectrum, some facilities have tight control with constant measurements, allowing for precise changes to be made. On the other end are greenhouses with no formal data collection. In this instance, changes to the environment are based on knowledge from a grower. This poises some facilities to be more easily adapted to the use of AI technology than others, based on their data collection infrastructure.

## OVERVIEW OF CEA FOOD SAFETY CHALLENGES

CEA is often framed as reducing or even eliminating traditional microbial food safety hazards due to the physical protection of the crop from the environment *(57)*, which is expected to lead to a lower likelihood of the edible part of the produce being in contact with wild animals and animal feces *(40)*. Supporting this, several authors have found lower total bacterial counts and lower microbiota diversity in crops grown in CEA systems compared to those grown in open fields *(32, 75)*. However, CEA clearly cannot produce products with "zero risk" of causing microbial or other food safety issues *(78)* and typical foodborne pathogens and perhaps unknown or waterborne pathogens are still a possible issue. Likely microbial food safety challenges in CEA include (i) pathogen contamination of inputs (e.g., seeds, substrates), (ii) pathogen contamination and persistence in water and water associated infrastructure, (iii) pathogen contamination and persistence in the overall facility infrastructure (e.g., conveyor belts, harvest equipment, trays/beds, floors), and (iv) risk of pathogen transfer throughout the system; due to the interconnectivity of hydroponics via water and general lack of full system sanitation, there is the regulatory issue of lot separation. Food safety risks in CEA are supported by a salmonellosis outbreak in the US in 2021, which was linked to CEA (specifically hydroponically) grown prepackaged salads *(14)*. While the outbreak strain was not recovered from inside the facility (it was found in an "outdoor storm water drainage pond beside the farm" *(14)*, the investigation of this outbreak did detect another *Salmonella* strain (serovar Liverpool) in an indoor pond that was used to grow lettuce. This illustrates that *Salmonella* represents a hazard that needs to be controlled and addressed in CEA agriculture. Additionally, in January of 2024, a recall of CEA (specifically greenhouse) grown prepackaged salads was reported due to possible contamination with *Listeria monocytogenes (27)*. A positive result for *L. monocytogenes* was identified during routine product testing. At the time in which this paper was written, no illnesses have been reported. Another microbial hazard that would need to be addressed (due to its presence in a wide range of sources, including natural environments), at a minimum, is enterohemorrhagic *Escherichia coli* (EHEC). Supporting the range of possible food safety hazards in produce, S*almonella, E. coli* O157:H7, human noroviruses and *L. monocytogenes* have all been identified on hydroponic produce *(43, 50, 59)*. While prevalence studies of foodborne pathogens have been performed in the production environment of open fields, as well as packinghouses and the processing environment of fresh-cut facilities *(5, 13, 64)*, more research to systematically assess food safety risks in the growing and harvesting of leafy greens under CEA systems is needed.

In addition to known foodborne pathogens, it also needs to be considered that pathogens that are not typically considered foodborne, as well as unknown pathogens, could be transmitted through CEA grown crops. Of special concern are emerging waterborne hazards (e.g., *Legionella)* that may be present in various water sources, which might be applied in CEA systems *(40)*. Particularly relevant is the recirculation of the nutrient solution in the hydroponic system. Water sources, such as municipal water, reclaimed water, and surface water, present differing levels of associated microbial risks, as each source varies in treatments and testing requirements, with municipal water typically considered the lowest risk *(33)*. Additionally, irrigation distribution networks could affect the water's microbial quality. For example, intermittent water supply (akin to the ebb and flow hydroponic technique) in India was found to have higher total coliform and *E. coli* counts at taps compared to levels taken from taps supplied with constant water *(41)*. Whether the system or equipment is temporarily or permanently assembled, the methods by which water storage, delivery, and distribution systems are cleaned, maintained, and stored are crucial. Given the range of possible microbial contaminants possible in CEA, more specific research clearly identifying microbial hazards and their frequency is needed for the CEA sector.

While growing media for hydroponics, aeroponics, aquaponics or soil-based growing systems vary widely and can provide avenues for contamination of final product, there is still limited research that would help with an assessment of risks associated with different inputs. Nutrient solutions, non-synthetic fertilizers (fish emulsion, algal extracts, liquid green waste extract), and non-soil growth media such as coconut coir or perlite are all examples of inputs used in CEA. Different CEA systems typically have specific requirements for handling of inputs to avoid cross-contamination. Notably, CEA that integrates fish (aquaponics) has a potential source of fecal contamination built into the production system. While there is some research regarding plant pathogens in soilless inputs *(12, 16, 44, 61)*, there is little research regarding the human pathogenic prevalence of CEA inputs. One study *(18)*, illustrated the role of substrates as a potential source of contamination in hydroponic systems, which can facilitate microbial transfer to harvested leaves. Similarly, Işık et al. *(39)* found that growth media used in soilless microgreen production can affect the transfer of pathogens to edible and inedible portions of microgreens. Due to the lack of knowledge surrounding the microbial environment of these inputs, combined with the wide range of inputs used and the different systems they are used in, there is a large knowledge gap regarding human pathogen microbial risks from risks from inputs and how inputs inputs facilitate the spread to edible or inedible portions of products *(37)*.

While automated systems can control seeding, planting, moving plants, irrigation (e.g., timed release and dosing of water and nutrients), harvesting, and post-harvest processing (e.g., moving growing trays pulled along a series of chains and pulleys, packing), these automated systems are often not hygienically designed or created with sanitation/disassembly in mind. This, combined with year-round production and limited sanitation (e.g., once a year), increases the potential risk of persistence and spread of pathogens. In addition, complex equipment and infrastructure in CEA may require extensive and well-managed maintenance to minimize food safety risks. In vertical farms, there are permanent structures with multiple growing levels. Equipment associated with growing includes multiple levels using shelving systems or vertically mounted growing systems (e.g., growing troughs suspended from the ceiling) and vertical conveyor systems *(23)*. Relevant to vertical farms, if any of the top layers become contaminated, there is a high likelihood that it could disperse via water droplets onto lower levels and onto edible portions of plants. Future research and development on hygienic design and sanitation in CEA facilities (including validation and verification) thus would be valuable *(37)*.

An additional challenge associated with microbial food safety in CEA is that there is limited knowledge of the microbiome within a CEA facility compared to a traditional agriculture microbiome. Plant microbiomes have been reported as playing important roles in securing food production and reducing microbial food safety risks *(11)*. For example, sensitivity to invasion by pathogens can be characterized by different states of plant microbiomes, i.e., the ones that are in dysbiosis and therefore sensitive to pathogen invasion vs. the ones that are in eubiosis and more resilient to microbial perturbations *(7)*.

Microbial interconnectivity between ecosystems plays an important role in the development of plant microbiomes and microorganisms can be transmitted via the internal compartments of seeds to mature plants *(58)*. Also, human pathogens can be transmitted via seeds to growing plants, although internal contamination with pathogens appears to be unlikely to occur *(69)*. A scientific opinion published in 2011 *(24)* hypothesized that the increased proliferation of inoculated Shiga-toxin producing *E. coli* (STEC) on hydroponically-grown microgreens could be potentially due to a less competitive microbiota. Hence, further research of the plant and overall environmental microbiome in CEA facilities, and the impact of microbiomes on food safety risks in CEA systems, may be valuable.

A specific operational challenge is that production in CEA facilities is essentially continuous, which means that it is typically difficult for facilities to define and validate a "clean break" between production lots. Supporting this, researchers hosting a two-day conference regarding food safety in CEA titled Strategizing to Advance Future Extension and Research (S.A.F.E.R.) in April 2023 identified a lack of clean breaks as a challenge that could be potentially mitigated with the use of Artificial Intelligence (AI) *(37)*. While there is no clear path to defining a clean break without full sanitation, AI-facilitated data analytics may be able to use regular (e.g., daily) testing data, as well as other data (e.g., sampling effort), to characterize the likely length of a contamination event although it is possible this could be underestimated due to the inherent rare nature of contamination events. This would be valuable as a lack of a break between lots can represent a substantial business risk as regulatory agencies (as well as customers) may, in case of a single contamination event (e.g., a product sample collected on a given day that tested positive for a pathogen), request and/or require clean breaks to agree on a recall that is limited to one day's production. Without a sanitation break to support that contamination would not have been carried over to subsequent days and lots (e.g., through water), it may be necessary to issue a recall that covers all products in the marketplace *(15)*. In some CEA facilities, production is only stopped once a year (which is when repairs and equipment cleaning occur); even then, full clean breaks may not occur, e.g., if water is not completely removed in deep water hydroponic systems.

Because CEA is a unique position between both primary producer and processer, the regulatory framework applicable to CEA is often unclear, leading to gaps in regulation and confusion for both regulators and industry. There however are already specific guidelines describing Good Agricultural Practices (GAPs) and Good Hygiene Practices (GHPs) for CEA facilities *(26)*, which include general recommendations such as: (i) protected facility structures should be located, designed and constructed to avoid contamination and harborage of pests; (ii) worker training and sanitation practices are necessary in all facilities; (iii) proper water management and soil amendment use are critical to controlling and reducing risks. Additionally, in the US, CEA firms are expected to adhere to the Food Safety Modernization Act (FSMA) and the Produce Safety Rule *(28)*. That being said, CEA is unique compared to the traditional produce supply chain because growing, harvesting, processing and packaging often occur in the same room or adjoining rooms, leading some firms to additionally be governed by the Preventive Controls for Human Food Rule *(29)* depending on their system. This can cause confusion from regulatory bodies and industry about what recommendations and frameworks apply, potentially leading to gaps in food safety and sanitation systems *(37)*. A related challenge is that CEA needs more guidance, as well as field-based assessments and data-based development of corrective actions, mitigations, responses to positive findings, including standardization of environmental monitoring programs (EMPs) for CEA *(2, 66)*. A specific challenge for EMPs in CEA is that it may be hard to distinguish between the different Zones, which define proximity to food (i.e., Zones 1, 2, 3, 4) *(60)*, as essentially all surfaces are connected via water recirculation. Formal risk assessments or risk ranking may thus be needed to rank food safety risks associated with CEA of specialty crops and to inform food safety regulations for CEA *(37)*.

Finally, in all food processing environments using human intervention, microbial and viral contamination via employees is a possible source. Personal hygiene and health requirements are critical as CEA personnel come directly in contact with edible and inedible portions of FVHs during seeding, and harvesting/packaging *(9)*. In many CEA facilities, Good Manufacturing Practices (GMPs) or GAPs are enforced, such as personal protective equipment (PPE) wearing and hand washing *(46)*; however, in some CEA facilities there may be a need to strengthen these practices.

## OPPORTUNITIES FOR DIGITAL AND AI TOOLS IN CEA FOOD SAFETY

There have been a number of exciting advances in the food safety applications of AI and digital tools, spanning both mechanistic (e.g., simulation and agent-based models) and data-driven approaches. Some of these tools have taken advantage of new real-time data streams, such as social media and mobile apps, or have benefited from other large scale data streams and technologies, such as next-generation sequencing (NGS), smart labels, and blockchain. The development of sensors and their integration with Internet of Things (IoT) technologies also provides an avenue for data streams that could be utilized by AI to manage food safety risks *(45)*. The application of these AI and AI-enabling technologies has shown promise in different areas, such as better pathogen detection and disease control. For example, BERTweet extracts foodborne illness-related entities from Twitter/X and was shown to identify unreported foodborne illness outbreaks *(67)*. A Bayesian hierarchical model was developed for real-time monitoring and nowcasting of foodborne disease cases from public health surveillance data *(72)*. Using *L. monocytogenes* in milk as an example, Njage at al. *(47)* demonstrated how machine learning (ML) can be used to predict stress phenotype components for new unknown pathogen strains given their whole genome sequencing (WGS) data, which could improve risk assessments for foodborne pathogens. Agent-based models (ABMs) developed to recreate a specific food facility, have provided facility-specific "personalized" food safety decision support for the food production environments *(76)*. A study by Nogales at el. *(48)* demonstrated the utility of neural models in optimizing the number of food safety inspections using data from the Rapid Alert System for Food and Feed (RASFF), which facilitates the exchange of information about health threats in European countries. Importantly, a number of peer-reviewed studies have developed and detailed specific tools that can be applied to CEA, including simulation-based and ML tools that can be used to predict food safety risks and facilitate improved control. For example, a series of papers *(3, 4, 65, 76)* has detailed how ABMs can be developed and used to facilitate improved control of environmentally transmitted foodborne pathogens. Also, a simulation model was developed to assess the listeriosis risk associated with a contaminated production lot of frozen vegetables *(77)* as an example of a decision-support tool for food safety and business management that can also be applied to CEA. Similarly, a number of different decision tree and ML-based methods have been applied to predict times and locations with an increased risk of pathogen contamination in fields and water sources *(62, 63, 73, 74)*; these approaches could also be adapted to CEA, even though input data would obviously be very different.

One key opportunity for digital and AI tools in CEA will be to integrate AI-based and digital food safety prediction and management tools into the overall digital infrastructure for CEA (i.e., systems that manage temperature, lighting, etc.). The ultimate goals of these efforts would be to (i) reduce food safety risks and manage them more effectively, (ii) minimize food safety-associated enterprise risks (e.g., by developing and implementing systems that can provide for validated "clean breaks" between lots), and possibly to (iii) provide enhanced transparency of food safety efforts to customers and possibly regulatory agencies. While these efforts will require (i) robust data acquisition systems and (ii) custom-tailored AI and digital tools, as detailed in the section above, existing tools that represent a starting point for these efforts already exist. Ultimately, proactive food safety systems for CEA could benefit from the development of comprehensive "digital twins" *(20)*, which would be individualized to each facility and be driven by real-time data to predict food safety risks. These digital twins could then be used to adjust food safety measures (e.g., testing frequencies, sanitation procedures, water treatment) to better control food safety risks and better manage situations with increased risk of pathogen contamination. Additionally, these models can also be complemented by various imaging or spectral based AI models to identify hot spots for organic build-up on diverse surfaces and Zones in CEA facilities *(25)*. A connection between AI models and microbial testing results can further aid in enhancing the relevance of these models for the assessment of food safety risks. This would allow CEA facilities to understand how different environmental and structural factors interact and affect the probability of foodborne pathogen (e.g., *Salmonella* and *L. monocytogenes*) contamination in different CEA facilities, and potentially reduce the cost of microbial sampling. Finally, these digital twins could be used to concurrently manage food safety as well as other outcomes such as quality, productivity etc., which could be used to optimize trade-offs between food safety, productivity, and quality. An example of such a trade-off is related to the negative impacts of high levels of chlorine that may be used, at the cost of quality, for water treatment and management of food safety risks. Additionally, combining models to manage food safety as well as quality and productivity will make it a more attractive product for the industry to implement.

More targeted food safety-related applications of AI in CEA could address the unique food safety challenges posed. Primary inputs (e.g., substrate, water, seeds) present a pathway of contamination in CEA, so the development of AI approaches based on imaging and spectral analysis of primary inputs used in CEA could enable validation of the quality and authenticity of them. Furthermore, these tools can also enable the evaluation of these primary inputs during storage and handling. Developing ML/AI tools based on predictive relationships between the imaging or spectral features of these primary inputs and microbial analysis could provide a potential surrogate marker for assessing microbial contamination *(52)*.

Water, as a critical primary input and route of widespread contamination, is an important point for microbial monitoring *(57)*. Microbial contamination of water can be addressed by developing a robust analysis of water quality and treatment of water. AI approaches can aid in automating the analysis of water quality, and develop predictive models of water quality for different seasons based on the geographical location and local water sources used for CEA operations *(30, 49, 68)*. In addition, AI approaches could also be developed to improve and evaluate the efficacy of water treatment technologies.

## CHALLENGES FOR AI TOOL APPLICATIONS TO FOOD SAFETY IN CEA

While there is enthusiasm for the use of digital and AI tools to improve food safety (e.g., the US FDA's "Food Safety Initiative") *(37)*, there are limited examples of successful practical applications of these tools to CEA food safety. Due to the relative newness of the CEA sector, a specific challenge faced by many firms is a lack of foundational food safety plans and systems *(37)*, which poses a major challenge for the application of AI for food safety. For example, many firms have not implemented stringent (or any) cleaning and sanitation breaks between growing lots and reuse substrates and water without treatments *(22)*. Furthermore, more automated systems that utilize moving trays with pulleys and motors (i) are rarely cleaned/sanitized and (ii) are manufactured in a way that makes equipment challenging to effectively clean (i.e., filled with hard to reach nooks and crannies, impossible to reach spots, difficult to take apart and put together) *(37)*. Lack of separation between growing and processing, and inadequate food safety knowledge commonly seen among startups and newer food industries also may represent a foundational challenge for some facilities. For facilities at earlier stages of their food safety maturity, it may not be appropriate to implement high tech data intensive AI strategies until appropriate foundational food safety practices are in place, including basic food safety training programs, which can be highly effective at reducing the risk of microbial contamination *(38)*. Additionally, creating AI models based on data gathered from initial CEA production systems that are lacking food safety foundations may create an inappropriate starting point for the modelling and AI-based data analytics efforts, as AI models would need to be fed new data and potentially reprogrammed to accommodate the changes that occurred after implementation of foundational food safety practices. However, even in the early stages of food safety system development, CEA may benefit from using existing pre-trained Large Language Models (LLMs), such as ChatGPT or Gemini, to support basic food safety tasks, such as personnel training and development of SOPs. While these models can streamline the tasks, expert reviews are recommended to authenticate the generated information.

Food safety data availability and quality are important factors for a well-trained and validated AI tool for food safety hazards management. In order to acquire the mass of data needed, a large amount of high-quality data is required to ensure AI's reliability; the only efficient pathway to this may often include data sharing between firms. This poses the challenge of data privacy hesitations. Food safety data are highly sensitive, due to fears of data abuse, bad publicity, reputation, liability, and the need to keep certain data (e.g., human illness data) confidential *(1, 53)*. CEA and other food companies can increasingly recognize the value of data sharing based on successes in other industries (from medicine to hospitality industries), where sharing of data has allowed scaling of AI applications and learning through peer networks *(53)*. Improved data sharing, including the use of shared data in AI models, has the potential to (i) provide food safety benchmarks for the industry and (ii) facilitate better business and food safety decisions. Thus, there is a need for research geared toward a better understanding of data sharing obstacles and the development of data infrastructure and algorithms that secure the privacy of users who engage in data sharing. One way of addressing this challenge is through Federated Learning (FL), which has gained attention in several domains *(8, 19, 21, 31, 70)*. In a federated environment, data remains secure within the physical location (i.e., data station) of its owners. Instead of transferring data, the model moves between these locations, effectively updating the model parameters from the data at the respective data stations, abiding by privacy principles. For example, Gavai et al. *(31)* developed a Federated Bayesian Network (BN) model to predict food fraud, which demonstrated the applicability of the federated BN in food fraud; they anticipated that such a framework may support stakeholders in the food supply chain for better decision-making regarding food safety control while still preserving the privacy and confidentiality nature of these data. In addition to the amount of data needed, the quality of data is also imperative. To preserve data quality, monitoring data needs to be consistent and standardized throughout the data collection period and even beyond the project time to enable a sustainable data source for further model improvement and validation. This can be challenging to apply from firm to firm as each company will have different data collection methods, data labeling, and different streams of data. This limits AI's applicability to the sector. While there is a growing trend of high-tech precision farms, there still remains a number of firms that use traditional produce growing and data monitoring methods such as pen and paper data collection. Some firms simply lack monitoring of growing variables altogether. A unique aspect of food safety data, especially microbial concentration data, is that contamination, while serious, is often rare. Contamination with pathogens would be typically detected in only a few samples, and the majority of the samples would be non-contaminated or contaminated below detection limits. These unbalanced datasets need to be handled carefully in the modelling process to reach a desired prediction accuracy for the positive samples.

It is important to realize the need to develop human resources in parallel with the development of technologies for improving the food safety of CEA-grown produce. This emphasizes the need for cross-disciplinary training between domain knowledge and data science/engineering disciplines. Additionally, to be able to leverage the full potential of AI technologies in CEA food safety, these technologies will need to present users with interpretable and useful information through an effective human-machine interface. Not only will users need to interpret results, but they will need to understand the models to address concerns about false positives and business liability as well.

Finally, to drive appropriate adoption of AI, economic aspects and costs and benefits of adopting AI systems may need to be quantified, including to understand opportunity costs that may be associated with implementing AI to help assure food safety (as there may be other food safety investments that generate a greater risk reduction in return for a given investment). Food safety is a unique business aspect because, while required, it is often seen as a cost center; a reduction in food safety risk rarely leads to a quantifiable direct increase in profits, but rather a reduction in potential capital lost through a food safety incidence (e.g., a recall). Research geared towards identifying a connection between reduction in food safety risk or recall risk and profits may help with decision making on AI implementation and incentivize companies to invest in shifting their food safety strategy towards AI and digital tools. At the same time, changes in the legal environment are needed to alleviate the barriers to adopting these technologies, for example to alleviate industry concerns about the potential increase in the liability and expense from using food safety predictions and knowledge generated by AI and digital tools *(1)*.

## CONCLUSIONS

While it is enticing to conclude that AI for microbial food safety is a wise application for CEA due to the industry's reputation as being "high-tech," there are still many challenges that need to be overcome prior to the adoption of this technology. Namely, there is an effort needed from academia and industry to (i) research and better understand the contamination sources, routes and microbial environment of known and unknown pathogens in a variety of CEA facilities, (ii) implement stronger, basic facility hygiene and sanitation practices and (iii) generate vast amounts of high quality data sources. Additionally, the creation of AI models needs to take into account the wide range of CEA facilities and data infrastructures and, through this, the vast amounts of private data required to be shared. While there are opportunities (such as the use of federated learning) to circumvent data privacy, the large majority of private firms are still reluctant to share confidential data. The range of CEA facilities not only makes it challenging to have one model fit multiple firms but it also poses the challenges of (i) data from different systems "being able to talk to each other" and (ii) application of AI models into systems with ranges of technological maturity. AI for microbial food safety in CEA is most likely utilized best towards specific food safety related challenges, such as validating clean breaks between lots, and allowing for targeted and specific microbial sampling plans to capture rare but serious contamination instances. Finally, it is important to remember that while AI can be seen as an attractive "fits all solution", food safety risks carry numerous interdisciplinary and intricate consequences for both firms and consumers, and ultimate decisions regarding such risks should be made by humans.


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