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Diffusion of innovation in controlled environment agriculture: A mixed-methods study of digital decision support tool adoption

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ABSTRACT

Controlled environment agriculture (CEA) enables farmers to manage all aspects of crop growing environments. However, the complexity of operations necessitates decision-support tools (DSTs) that integrate and analyze large datasets for optimized management. Despite their benefits, the adoption of DSTs is influenced by factors beyond technical effectiveness, such as cost, usability, and perceived value. This study aimed to evaluate the experiences and perceptions of CEA operators regarding DSTs, identify barriers to adoption, and determine the characteristics necessary for widespread acceptance, using the Diffusion of Innovation Theory as a framework. A mixed-methods approach was employed, consisting of a survey of 44 CEA operators across the United States by in-depth interviews with 14 respondents. The survey and interviews explored DST experiences, concerns, and desired features, with data analyzed using thematic analysis. Farmers desired general farm management tools that could be easily customized to their specific needs and operations. Key preferences included seamless data integration across tools, automation, and Artificial Intelligence (AI) integration for predictive modeling and decision suggestions, while maintaining human oversight. Cost and trialability were major barriers, with farmers requiring financial benefits that outweigh costs. Complexity of use and incompatibility with existing workflows were significant deterrents to adoption. The findings underscore the importance of user-centered design, financial feasibility, and demonstrable tool performance. This study highlights critical factors influencing DST adoption in CEA and provides actionable insights for developers to design tools that are cost-effective, user-friendly, and customizable. Addressing these barriers can enhance adoption rates and optimize farm operations, ultimately advancing the CEA industry.

Introduction

Digital decision support tools (DSTs) have become an integral part of Agriculture 4.0, enabling farmers to optimize their operations more effectively based on real-time data. Digital DSTs are software-based tools that help users make decisions aimed at achieving desired outcomes and minimizing risks (Rose et al., 2016), such as by providing insights on historical data or using current or predicted conditions to aid management planning. DSTs can integrate and analyze large volumes of data from various sources, providing farmers with actionable insights that optimize resource use and enhance productivity. As a result, they have been shown to improve yields and profits in traditional agriculture by providing data-based insights that allow more informed decision-making (Zhai et al., 2020).

DSTs are particularly useful for controlled environment agriculture (CEA) operations, such as greenhouses (GH), container farms (CF), and plant factories (PF). CEA can achieve a higher level of environmental control during crop production than field farming by allowing farmers to directly control light intensity, light quality, temperature, humidity, carbon dioxide (CO_2) levels, nutrient content, and irrigation through the use of indoor equipment, climate control, and artificial lighting. While greater control in CEA can often result in higher yields and greater

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resource use efficiency compared to traditional agriculture (Orsini et al., 2020), it also requires farmers to make decisions on almost all environmental factors, rather than the select few that conventional farmers have control over.

Determining optimal conditions requires extensive horticultural and technological knowledge, and inefficient management strategies can result in reduced yields or wasted resources, leading to lost revenue. For example, one indoor farm in Sweden had to sell its lettuce at half the expected price during its first harvests due to inefficient settings for irrigation, nutrition, seeding depths, and lighting schedules (Milestad et al., 2020). While this farm was able to recover in future cycles, these losses can be consequential for farms operating on small margins. In CEA operations, each condition must be chosen and closely controlled by the operator, which can become time-consuming and tedious. This requirement for quick but precise control makes DSTs particularly helpful within this field.

While DSTs have demonstrated several benefits, the effectiveness of an individual tool, especially when demonstrated primarily in a research setting, does not always translate to high adoption rates among users (Rinaldi & He, 2014). In 2017, 45 % of small farms (less than 10,000 sq ft) relied solely on pen and paper for production and inventory management. However, the same year, 71 % of growers believed their yields would improve with data analytics, and 43 % believed they could save money with management software (2017 State of Indoor Farming Report, 2017). This suggests a desire for DSTs, but there is a lack of literature exploring the causes and barriers to adoption, as well as recent studies assessing the current state of adoption within the field. Existing studies on DST adoption in agriculture have been largely reserved for conventional land farming fields (Thomas et al., 2023), which can be considered a separate market from the CEA field due to its technological and cultural differences.

To frame our investigation into the factors influencing the adoption of DSTs in CEA, we apply the Diffusion of Innovation (DOI) Theory (Rogers, 2003) as our guiding theoretical framework. This theory is widely used in agricultural technology adoption research, providing a structured lens through which to examine how, why, and at what rate new innovations, such as DSTs, are adopted within a social system. DOI focuses on the characteristics of the innovation itself, specifically five core attributes that influence adoption: relative advantage, compatibility, complexity, trialability, and observability. These dimensions are particularly relevant in the CEA context, where DSTs must not only demonstrate clear benefits over existing tools but also align with users' operational workflows, technical literacy, and economic constraints. CEA operators must manage a high volume of data and make constant, high-stakes decisions, meaning that innovations must be intuitive, efficient, and demonstrably effective to be viable. Moreover, the DOI theory's classification of adopters, from innovators to laggards, provides insight into the varied readiness levels among growers, which can inform design and rollout strategies for new tools. Previous studies have applied DOI to understand DST adoption in conventional agriculture (Looney et al., 2022; Shang et al., 2021), but few, if any, have explored its applicability in the technologically distinct and rapidly evolving CEA space. As such, DOI theory provides a well-established yet underutilized framework for better understanding innovation adoption dynamics in this context and for informing the design of DSTs that are more likely to be accepted, retained, and effectively utilized by CEA operators.

This paper seeks to build off the discussions introduced in the previous paper in this series, Lindow et al. (2025), where surveys and interviews of CEA operators across the United States were conducted. This previous work identified the challenges CEA operators found most difficult to make decisions on, as well as the factors that most influenced their management decisions. We also found that a majority of CEA operators utilize DSTs to address specific challenges or enhance overall farm management, and most operators expressed positive views of DSTs, even among non-users. These findings highlighted the impact, implementation, and successes of existing DSTs in enhancing operational effectiveness and identified areas where future DST development could further benefit farmers. However, not all tools were viewed equally by all operators, with current DST users often having abandoned previous tools, citing difficulties with over-complexity, cost, time-consuming data entry, and inaccuracies.

Here, we further examine the survey and interview findings to identify additional barriers and requirements for DST adoption among CEA operators. This study aims to gain a comprehensive understanding of operators' opinions, considerations, and concerns, which will inform the development of new digital DST tools that are more desirable and marketable, ultimately enabling farmers to more effectively achieve their yield and profit goals. The primary objectives of this paper are to assess the innovation factors of DSTs in CEA that encourage or discourage adoption and to use these results to make recommendations for features and considerations in DST development. The results of this research are expected to provide insight into the characteristics of DSTs that would be most beneficial and appealing to CEA operators and provide direction for future industry development and research focus.

Literature review

Diffusion of innovation theory and related frameworks

Social and behavioral theories can provide direction to evaluation approaches in technology adoption research. Many theories and models exist to describe technology adoption; however, some of the most prominent theories in the agricultural realm are the Theory of Planned Behavior, the Technology Acceptance Model, and the Diffusion of Innovation Theory (El Bilali et al., 2021).

The Theory of Planned Behavior (TPB) describes human behavior as a result of beliefs, attitudes, and intentions (Ajzen, 1991). For example, (Hou & Hou, 2019) used TPB to assess how different groups in China made decisions about adopting low-carbon agriculture. The Technology Acceptance Model (TAM) explains how potential users become aware of, accept, and eventually come to use new technology as a function of perceived usefulness and ease of use (Davis, 1989). Khoza et al. (2021) used TAM to assess how differences in perceptions between men and women impacted each group's adoption of climate-smart agriculture technology, highlighting the model's use for identifying adoption factors on an individual level. Mohr and Kühl (2021) used TAM with TPB to identify factors influencing Artificial Intelligence (AI) acceptance amongst German farmers. The researchers chose these theories due to their application for earlier stages of adoption research (the acceptance stage), which was appropriate for the paper since most agricultural AI technology was still a prototype. Either of these theories could help researchers understand what beliefs influence DST adoption, and thus, interrogate beliefs or attitudes that could or must be changed to increase adoption.

While TAM and TPB are focused on predicted behavior and attitudes towards technologies, the Diffusion of Innovation (DOI) Theory focuses instead on the characteristics of the technology itself (Rogers et al., 2008). DOI explains the factors of the technology that influence the likelihood and rate at which new technologies spread. This theory categorizes populations into five groups based on their receptivity to adopting an innovation: innovators, early adopters, early majority, late majority, and laggards. Innovators are the first to adopt a new technology, while risk-averse laggards are the last. DOI also proposes five characteristics of an innovation or new technology that impact potential users' willingness to adopt it:

- **Relative advantage:** Is the technology better than the idea, program, or product it replaces?
- **Compatibility:** Is the technology consistent with the user's needs, values, and past experiences?
- **Complexity:** Is the technology easy to understand or use?

- **Trialability:** Can the technology be experimented with/trialed before making a full commitment?
- **Observability:** Does the technology have results that can be observed?

This theory has been used to investigate DSTs and technology in conventional agriculture. For example, Ranjan et al. (2022) used DOI to explore the readiness of adoption for the Agricultural Conservation Planning Framework in the United States Department of Agriculture, and Mahamood et al. (2016) used the theory alongside the Unified Theory of Acceptance and Use of Technology (UTAUT) to investigate low adoption of communication technology among Malaysian farmers.

TPB, TAM, and similar theories, such as UTAUT and the Theory of Reasoned Action (TRA), are well-suited to guide policies and programming aimed at altering social attitudes toward an innovation due to their focus on the individual. Meanwhile, theories like DOI, with its focus on the innovation itself (or the environment surrounding the individual), are better suited to guide technology and environmental development (Croyle et al., 2005). However, all of these theories contain overlapping constructs and ideas (Kim & Crowston, 2011). To the authors' knowledge, no existing literature applies any of these theories to innovations in the CEA space, as determined through searches of various research databases.

Given this gap, our study adopts the DOI theory as the central framework for examining digital DST adoption in CEA. DOI theory has been widely applied in agricultural research to explore how innovations spread, emphasizing five key characteristics —relative advantage, compatibility, complexity, trialability, and observability —that influence the likelihood of adoption. These are particularly relevant in the CEA context, where DSTs must be both technically effective and practically usable in highly controlled and data-intensive environments. Prior applications of DOI in agriculture have identified key adoption barriers, such as tool complexity and poor fit with farmer workflows (Looney et al., 2022) and have modeled digital adoption scenarios using agent-based simulations (Vinyals et al., 2023). By focusing on the characteristics of DSTs and how they align with user needs in CEA, DOI provides a robust framework to uncover not only which tools are adopted but also why certain tools succeed or fail in this unique agricultural environment.

Agricultural decision support tool development

Digital decision support tools in agriculture can range from simple to highly complex. Some tools provide tailored recommendations based on user input, while others may simply showcase potential outcomes without offering any guidance. Low-complexity DSTs may include simple visualizations of historical data, which farmers can use to assess the efficiency of their operations on their own, while more advanced systems support real-time decision making with predictive modeling dependent on sensor data. However, these more advanced systems also require greater data integration and interpretation methodologies to enhance the usability and practicality of these tools (Shang et al., 2021; Zhai et al., 2020).

In agriculture, it is essential to train farmers in effectively using new digital smart tools, as not all tools are intuitive for new users (Weersink et al., 2018). There is a low adoption rate of DSTs among farmers in general, often due to the complexity of these systems, farmer preference for independent decision-making, and the need for significant initial investment in technology and training (El Bilali et al., 2021; McCown, 2002). Numerous studies have further investigated the under-utilization of DSTs and the factors influencing it in conventional agriculture, with most concluding user-friendliness, costs and profits, credibility, and user knowledge as prominent factors (Hochman and Carberry. 2011; Kerr, 2004; Rose et al., 2016; Rossi et al., 2014). Rossi et al. (2014) defined strategies for addressing these issues during the design and development process of DSTs, including steps guided by communication with potential users, consideration of ease of use, establishing compatibility with user needs and resources, and taking a holistic approach to design. However, a review of DST adoption research in precision agriculture identified a notable gap, with no existing studies evaluating the relevance of farmer needs, values, goals, social networks, and learning styles on adoption (Pathak et al., 2019). Recent studies have reinforced these conclusions, emphasizing the importance of integrating DSTs with existing farm operations and the need for localized, user-centered design approaches (Dissanayake et al., 2022; Shang et al., 2021).

Comparable studies in the CEA field are scarce. Schmeitz (2023) conducted a case study on one digital DST for CEA growers in three regions. Their conclusions emphasized the need for greater understanding by developers of the needs of specific users, resources, desires, and concerns to fully support audiences and ensure tool adoption. Yet, thus far, there have been no studies on influencing design factors for DST adoption in the CEA field. Rose et al. (2016) identified age, farming type, business scale, and IT education as modifying factors that influence the strength of the influencing factors for adoption in traditional agriculture. Since many of these modifying factors may differ on average between CEA and traditional agriculture, both due to the advanced technological nature of these farms and the comparative newness of the field as a whole (Dohlman et al., 2024), it can be expected that the most relevant factors limiting DST adoption in CEA cannot be wholly understood by research conducted solely on traditional agriculture.

Controlled environment DST applications

In CEA, DSTs such as Link4 (Link4 Corporation, Anaheim, CA) and Farmhand (Freight Farm, Boston, MA) utilize data collected by the Internet of Things, which includes environmental sensors that measure temperature, humidity, CO_2, and light intensity. Other DSTs, such as AgriERP (Folio3 Software, San Mateo, CA) and Artemis (Artemis, Seattle, WA), include labor and crop tracking data to document farm activities, including watering, transplanting, and integrated pest management (IPM) implementation. Crop, financial, and environmental data, once uploaded to the DST either manually or automatically, can then be used in several ways depending on the DST's complexity. Some DSTs present data that the operator can analyze for trends themselves or use simple decision trees to provide direction. More advanced DSTs like Priva (Priva, De Lier, Netherlands), however, use machine learning algorithms to process the data, which can give deeper and quicker insights, leading to more effective farm management in areas such as climate control, irrigation management, and crop scheduling (Shang et al., 2021; Zhahir et al., 2024).

Little data is publicly available on the adoption of DSTs in this field. The most recent industry report that indicates the state of DST use was the 2017 State of Indoor Farming Report (2017 State of Indoor Farming Report, 2017). However, the reported data is expected to differ from the current state, as according to more recent reports, the industry has been growing rapidly within the last decade (2024 Global CEA Census, 2025; Dohlman et al., 2024). The 2024 Global CEA Census categorizes DSTs together with control software (i.e., tools that enable remote control of equipment without collecting data on historical use), which complicates the identification of specific adoption rates of DSTs. However, overall results indicate a desire for the adoption of new technology in general (2024 Global CEA Census, 2025).

Methods

This research was conducted as an explanatory sequential mixed-methods study, wherein we surveyed CEA operators throughout the United States to inform the design of semi-structured interviews with operators from the respondent group. This methodological design was chosen to allow the interviews to be narrower and more targeted in their scope, thereby enabling us to optimize the qualitative assessment for the most useful and in-depth analysis.

In this study, DSTs were defined to participants as "any digital software (online platform, app, etc.) used to improve or enhance farm management, including models, documentation, monitoring, analytics, or controls." Both the survey and interview questions were developed by the research team using the DOI Theory as a framework, with questions conceptualized to target respondents' opinions related to the five characteristics of innovation described by this theory (relative advantage, compatibility, complexity, trialability, and observability). The DOI Theory was chosen due to its applicability in exploring implementable concepts in technologies and guiding tool development more directly (García-Avilés, 2020). Designing and discussing the interviews through this lens enables us to consider potential explanations for why some tools may be more successful in the CEA industry than others, as well as which characteristics DST developers should consider or adjust for future innovation.

The survey included 31 questions and was created using Qualtrics (Qualtrics Software, Provo, UT, 2020). The survey posed two purposes. The first step was to collect pre-screening information about the respondents' farms of employment (number of employees, crops grown, system types, and age of operation) and the respondents themselves (demographics and farming experience) to inform the selection process for the subsequent interviews. The second objective was to gather basic and quantitative data on respondents' experiences with decision-making and DSTs on their farm, which were used to inform the focus of the interview questions. These experiences were then explored in-depth through qualitative assessment during the interviews.

The interview questions aimed to delve deeper into the operator's farm challenges and decision-making processes, DST experience and opinions, barriers to adopting new tools, and DST feature preferences. Based on survey responses, the interview protocol was adjusted to address two groups differently: those who reported using at least one DST in their farm (Group 1) and those who did not (Group 2). A bonus question was added for interviewees who stated on the survey that their farms previously used a DST that they no longer use to explore what characteristics might result in abandonment despite farmers' initial interest in a tool. Two operators running a CEA farm at a University of Florida research facility evaluated the survey and interview questions for content validity and understandability. According to the team's feedback, new options were added for several multiple-choice questions, and some questions were rewritten to improve clarity. A summary of the final interview protocol is shown in Appendix A.

The survey was sent to 182 CEA farmers throughout the United States between September and November 2023. This study was limited to US-based companies only due to both practical recruitment reasons and for market consistency, as varying regulatory contexts, economies, and climates between countries could impact the interpretability of results. Thirty-seven of the contacted farmers were obtained from a referral sample, which is the recommended process for difficult-to-reach populations (Goodman, 2011). These referrals came from six faculty members and three graduate students at the University of Florida with experience in the CEA industry or with CEA operators. The remaining 145 contacts were identified using purposive sampling to identify participants operating commercial or non-profit CEA operations within the United States. This was done by searching publicly available sources using the terms "indoor farm" and "greenhouse" in combination with the name of each U.S. state. This approach ensured geographic coverage across the country and allowed for the inclusion of diverse business sizes and crop types. While this approach may exclude operations without a digital presence, it aligns with established mixed-methods research practices for studying specialized populations (Rai & Thapa, 2015).

The survey received 44 responses. This value is comparable with other surveys in the CEA industry, with response numbers from US CEA producers ranging from 42 to 74 in the five years up to our study dates (2019 Global CEA Census, 2019; 2020 Global CEA Census, 2020; 2021 Global CEA Census Report, 2021; Walters et al., 2020). Between October and November, 22 of these respondents were asked to participate in an interview. The selection process aimed to select a group of farmers most likely to represent the overall experiences of the CEA industry. Thus, interviewees were chosen based on the approximate distributions of climate areas, system types, ages, prior farming experiences, and current and former use of DSTs, as identified in the survey responses. Ultimately, 14 interviews were conducted between October and December 2023 on Zoom video conferencing software (Zoom Video Communications, San Jose, CA). Ten interviews were conducted with individuals who currently use DSTs (Group 1), and the remaining four were with those operating without DSTs (Group 2). This approximated the ratio of users to non-users identified in the survey. Each interview lasted between 10 and 84 min. Six interviewees were asked the bonus question regarding why they stopped using a DST, including two who did not mark doing so on the survey—one who recalled prior use during the interview, and another who switched tools shortly after completing the survey. All interviews were recorded and transcribed using the transcription tool Otter.AI (Otter.AI, Mountain View, CA), which was corrected for mistakes by two members of the study's team.

Corrected transcripts were analyzed using NVivo qualitative data analysis software (NVivo 14, Denver, CO, 2023). Two members of the research team examined the interview transcripts using thematic analysis (Nowell et al., 2017), employing a combination of inductive and deductive approaches (Northcutt & McCoy, 2004). Prior to analysis, the research team compiled a list of deductive codes related to anticipated responses to the interview questions and keywords drawn from the DOI theoretical framework. Additional inductive codes emerged during the coding process, as both reviewers individually read transcripts line by line and identified unanticipated recurring ideas. Related codes were organized hierarchically into categories, with relationships between codes determined by conceptual similarity and alignment with DOI attributes. This process enabled the integration of both theory-driven and data-driven insights into the final thematic structure, and a third research team member confirmed the coding accuracy of the first two coders to ensure further consistency.

During analysis, interview themes were compared with survey patterns to identify areas of convergence and divergence. This integration of quantitative and qualitative findings enabled a more comprehensive understanding of the factors influencing DST adoption than either method alone. The research conducted in this study received approval from the University of Florida Institutional Review Board (Protocol No ET00018995).

Results

Representation and respondents

Tables 1 and 2 show the survey respondents' farm characteristics and demographics, respectively. Note that some farms used multiple growing methods and/or multiple system types. The characteristics of the interviewee's farms, as well as their background and demographics, are detailed in Table 3. Of 44 respondents, 68.1 % ($n = 30$) currently use at least one DST on their farm. Additionally, 34.1 % ($n = 15$) of respondents abandoned a DST at some point during their farm's operations (including one interviewee who only recalled rejecting a previously implemented DST during their interview).

Each interviewee was assigned a fictional pseudonym to maintain anonymity. Interviewees were asked about their prior experiences in CEA, including their job title and form of employment, before their current role. For several, their current farm was their first experience in horticulture or agriculture, coming from backgrounds such as sales, marketing, technology, and medical research. These people generally cited inspiration to open a CEA farm after finding an interest in the subject or identifying an untapped or underserved market in their area. This trend is consistent throughout the industry, with at least 41 % of CEA founders having no prior agricultural experience, according to global surveys conducted between 2019 and 2021 (2019 Global CEA

Table 1
Characteristics of survey respondent farms ($N = 44$).

Variable	n	(%)
Crop types		
Leafy greens	37	84 %
Microgreens	27	61 %
Herbs	21	48 %
Vine vegetables	11	25 %
Berries	3	7 %
Mushrooms	3	7 %
Nursery starts	3	7 %
Other[a]	7	16 %
Growing methods		
Hydroponics	37	88 %
Aquaponics	9	21 %
Aeroponics	2	5 %
System types		
Greenhouse	21	48 %
Container farm	10	23 %
Plant factory	18	41 %
Number of employees		
1–3	14	32 %
4–6	12	27 %
7–9	2	5 %
10–19	0	0 %
20–49	12	27 %
50–99	0	0 %
100+	4	9 %
Operational age		
2 or fewer	9	20 %
3–5	16	36 %
6–10	12	27 %
More than 10	7	16 %
Region[b]		
Southern	15	34 %
Central	20	45 %
Northern	9	20 %

[a] Other crop types included squashes or gourds, tree fruits, ornamental plants, aloe, ginger, turmeric, cannabis, edible flowers, succulents, and root vegetables. Two or fewer respondents reported each of these crop types.
[b] Farm regions are grouped based on the International Energy Conservation Code (IECC) climate zones. “South” refers to zones 1–3, “Central” includes zones 4–5, and “North” includes zones 6–7 (International Code Council, 2012).

Table 2
Survey respondent demographics, positions, and experiences.

Variable	n	(%)
Total years of agricultural experience (N = 42)		
Less than 2	2	5 %
2–5	15	36 %
6–10	16	38 %
11–15	3	7 %
16–20	2	5 %
21–30	1	2 %
31+	3	7 %
Years at farm (N = 42)		
Less than 2	8	19 %
2–3	3	7 %
3–5	13	31 %
6–10	12	29 %
11–15	3	7 %
16–20	1	2 %
21+	2	5 %
Title (N = 42)		
CEO, Founder, or Owner	17	40 %
Senior Management	9	21 %
Head Grower or Operations / Production Manager	10	24 %
Other	6	14 %
Highest Degree (N = 42)		
Bachelor’s degree	26	62 %
Master’s degree	9	21 %
Doctorate degree	3	7 %
Some college credit (no degree)	2	5 %
High school graduate, diploma, or equivalent	1	2 %
Associate degree	1	2 %
Race (N = 42)		
American Indian or Alaska Native	0	0 %
Asian	0	0 %
Black or African American	1	2 %
Native Hawaiian or Other Pacific Islander	0	0 %
White	37	88 %
Other	3	7 %
Prefer not to answer	1	2 %
Ethnicity (N = 42)		
Hispanic	5	12 %
Not hispanic	35	83 %
Prefer not to answer	2	5 %
Gender (N = 41)		
Man	22	52 %
Woman	18	43 %
Non-binary	1	2 %
Age (N = 42)		
20–29	9	21 %
30–39	14	33 %
40–49	10	24 %
50–59	4	10 %
60–69	4	10 %
Over 69	1	2 %

Census, 2019; 2020 Global CEA Census, 2020; 2021 Global CEA Census Report, 2021). Though nearly all interviewees obtained at least a bachelor’s degree, the subjects varied, ranging from horticulture and plant sciences to psychology and environmental science. Two interviewees without prior agricultural or horticultural backgrounds noted taking college courses or attending a 3-month hydroponics program before opening their current farm. Other interviewees either have a more extended work history in greenhouses, aquaculture, or hydroponics, or a family history of conventional farming.

Adoptability of new tools

Survey respondents were asked to self-report their willingness to adopt new technology, based on the descriptions of adopter groups from the DOI theory:

- **Innovators:** I am very likely to adopt a new technology as soon as it becomes available.
- **Early adopters:** I am likely to adopt a new technology after I have seen it used by others and have heard good things about it.
- **Early majority:** I am likely to adopt a new technology after it has been around for a while and I have had a chance to learn more about it.
- **Late majority:** I am likely to adopt a new technology after it has become the standard and I am forced to use it.
- **Laggards:** I am very unlikely to adopt a new technology.

Survey respondents generally considered themselves ahead of the curve in terms of their willingness to adopt new technology, regardless of whether their operation used DSTs (Fig. 1). As discussed in the previous paper in this series (Lindow et al., 2025), the survey identified a notable trend with newer operations adopting DSTs at higher rates than the oldest operations (100 % adoption amongst operations 2 years or younger, versus only 14.3 % adoption amongst operations over 10 years old). The paper also noted that CFs were more likely to use digital DSTs (90.0 %) than PFs (66.6 %) or GHs (61.9 %). This could be linked to the fact that older operations were more likely to be GHs than PFs or CFs, with GHs accounting for 57.1 % and 75 % of systems over 5 and 10 years old, respectively, and no CFs exceeding the 6–10-year age range. However, the youngest operations were also twice as likely to have abandoned a previous tool (33.3 % for operations 2 years or younger versus 16.7 % for operations 10 years or older). In comparison, GHs were more likely to have abandoned a DST (44.4 %) than either PFs (37.5 %) or CFs (33.3 %).

The DOI framework describes the adoption process as five stages: knowledge, persuasion, decision, implementation, and confirmation.

Table 3
Interviewee demographics and farm characteristics.

Pseudonym	Title	Years with the farm	Currently using DST(s)?	Region[a]	Number of employees	Crops	System type(s)	Growing method(s)	Highest degree	Age	Gender
Arthur	CEO, Owner, or Founder	2–3	Yes	South	1–3	Leafy greens, Herbs, Microgreens	Plant factory	Aquaponics	Doctorate degree	Over 69	Man
Sophie	CEO, Owner, or Founder	6–10	No	North	1–3	Leafy greens	Container farm(s)	Hydroponics	Bachelor's degree	40–49	Woman
Ellis	Senior Management	11–15	No	Central	7–9	Leafy greens, Herbs, Microgreens, Mushrooms, Nursery starts, Other	Plant factory	Hydroponics, Aquaponics	Bachelor's degree	30–39	Non-binary
Emmett	Senior Management	6–10	Yes	South	4–6	Leafy greens	Greenhouse	Hydroponics	Bachelor's degree	30–39	Man
Kira	Head Grower or Operations/ Production Manager	3–5	Yes	North	20–49	Leafy greens, Herbs, Microgreens	Container farm(s)	Hydroponics	Master's degree	30–39	Woman
Neil	Senior Management	6–10	Yes	Central	100+	Leafy greens, Herbs, Microgreens	Plant factory	Hydroponics	Bachelor's degree	30–39	Man
John	CEO, Owner, or Founder	3–5	Yes	Central	1–3	Microgreens	Container farm(s)	Hydroponics	Bachelor's degree	20–29	Man
Abbey	Head Grower or Operations/ Production Manager	3–5	No	Central	4–6	Leafy greens, Herbs, Microgreens, Other	Plant factory	Hydroponics	Master's degree	20–29	Woman
Rory	Head Grower or Operations/ Production Manager	Less than 2	Yes	North	4–6	Microgreens	Container farm(s), Plant factory	Other[b]	High school graduate, diploma or equivalent	20–29	Man
Connor	Senior Management	6–10	Yes	South	100+	Leafy greens, Vine vegetables, Berries	Plant factory	Hydroponics	Master's degree	40–49	Man
Sadie	CEO, Owner, or Founder	3–5	Yes	Central	1–3	Microgreens	Container farm(s), Plant factory	Hydroponics	Bachelor's degree	30–39	Woman
Hugo	CEO, Owner, or Founder	Less than 2	Yes	South	1–3	Leafy greens, Herbs, Microgreens	Container farm(s), Plant factory	Hydroponics	Bachelor's degree	30–39	Woman
Ray	CEO, Owner, or Founder	3–5	Yes	Central	7–9	Leafy greens, Mushrooms	Greenhouse, Container farm(s), Plant factory	Hydroponics	Bachelor's degree	40–49	Man
Jason	CEO, Owner, or Founder	3–5	No	Central	1–3	Leafy greens, Herbs, Microgreens, Berries, Mushrooms, Nursery starts, Other	Greenhouse	Hydroponics, Aquaponics	Master's degree	60–69	Man

[a] Farm regions are grouped based on the International Energy Conservation Code (IECC) climate zones. "South" refers to zones 1–3, "Central" includes zones 4–5, and "North" includes zones 6–7 (International Code Council, 2012).
[b] The survey options included hydroponics, aquaponics, and aeroponics. However, Rory's company website confirms that their operation uses soil-based growing methods only.

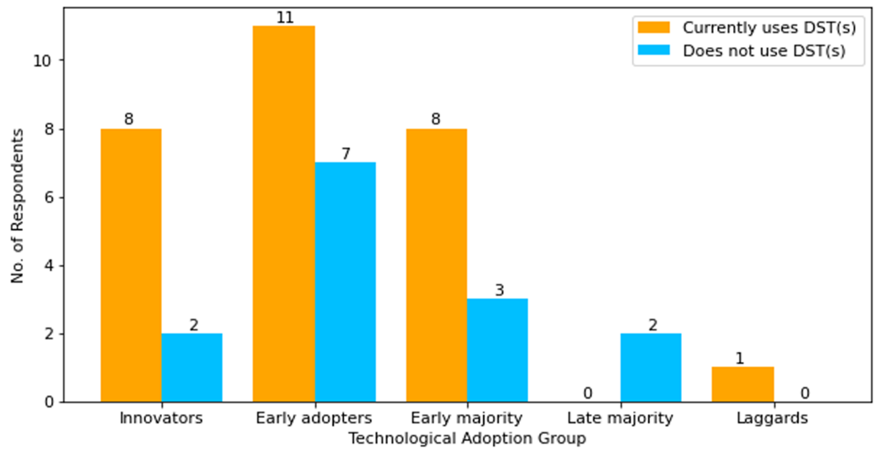

Fig. 1. Survey respondents' technological adoption based on self-reported willingness to adopt new technology.

Current users are in the confirmation phase, having either decided to keep or replace their implemented DSTs with another commercial tool or a self-made tool. However, of all survey respondents who chose to adopt a DST at any point in time, 15 (48.4 %) had implemented but abandoned a tool, i.e., rejected it at confirmation. However, all but one eventually replaced this rejected tool. While two non-user interviewees discussed not knowing their options or how to implement DSTs, all non-users held generally positive opinions and expressed interest in potential adoption of DSTs, with one even planning to adopt in the near future. This suggests that many non-users are in or have passed the persuasion phase regarding DSTs in general, although they are earlier in the process with specific tools. Sophie and Ellis had both previously been in the decision phase for individual tools, but ultimately chose to reject them.

When asked to rate the importance of each DOI element, given the descriptions bulleted in Section 1, every aspect averaged between 4.2 and 4.3 out of 5, indicating a relatively high desire for each with slight preference between the elements, with no statistical differences in ranking between system types, operational age, or farmer demographics. As this quantitative data is a result of self-reporting rather than tracking adoption habits, these responses may contain bias and thus should not be taken conclusively. While this information points towards a field of operators eager to adopt new technology with equal concerns for all DOI elements, the qualitative data obtained in the interviews can better identify and explain the nuances associated with each element as relevant to DST development and adoption. This section explores these concepts in greater detail based on the interviewee's responses to better understand how these characteristics impact willingness or hesitancy to adopt.

Relative advantage

Relative advantage refers to the characteristics that make the new DST superior to the product it replaces. Cost was the most significant limiting factor to new tool adoption, mentioned as a barrier by 11 of 14 interviews. This aligns with the 2024 Global CEA Census results, which declared "cost and affordability" as the greatest hindrance to technology implementation in the field (2024 Global CEA Census, 2025). However, this could be overcome for certain interviewees if the tool has a significant enough advantage over other tools or if it is used without any tools, i.e., if they perceive it as cost-effective. Interviewees overall want a tool that will lead to higher profits than it costs or save on other essential resources, such as time and labor.

Reliability also factors into how advantageous users consider the tool. Users want to know not only that the DST will work how it's supposed to, but that it will continue to work for a significant time. Ellis, who has over a decade of experience running a plant factory, noted that if, within a few years, the tool breaks or stops being supported by its creators, users may not see the worth. Users may also not rely on a DST for all areas of their operation, but may find particular benefits in using the tool for tedious tasks. For example, Arthur, a producer of microgreens and leafy greens, preferred manually checking products for visual quality, size, and other factors, but relied on a tool for counting lettuce heads and collecting quantitative data that would have required more time and mental effort through manual collection.

Larger and more profitable operations are generally more flexible in making significant upfront purchases, especially when they anticipate a long-term return on investment. In contrast, smaller operations tend to be more cautious, as they may lack the funds to sustain themselves long enough to realize a positive ROI. Therefore, past a specific price point, the relative advantage of a tool must be greater for smaller companies to adopt than for larger ones.

For a tool to be successfully adopted, it must offer a clear advantage not only over existing alternatives but also compared to not using any tool at all. For example, one interviewee stopped using a previously employed tool because it required excessive time for data entry, ultimately leading to more time spent than if no tool had been used at all. Additionally, interviewees may perceive little incentive to adopt a tool that merely replicates tasks they can perform by hand, especially if the time savings are not substantial.

> "A decision tree or decision model that answers simple questions that you don't really need a whole software program for, that wouldn't do much good for us, because we can do that ourselves." – Jason.

What a "relative advantage" is to users may differ based on priorities. For example, multiple interviewees requested access to their historical data, but Arthur specifically stated that they did not. Instead, this farmer only cared about the day-to-day decisions, noting that if they had an IoT system that could automatically record it all, while that would be helpful to researchers or other farmers, it was not high on his priority list because "it doesn't necessarily add to the bottom line." To this end, some users may not find the data collection by the DST useful if it does not also prompt action. For those with employees or teams dedicated to data analysis, new data or visualization can be sufficient for DST adoption; however, smaller farms without these analysts may be hindered by the extra time and energy required for data-based decision-making. According to the 2016 State of Indoor Farming, small farms under 0.15 acres spend significantly more of their time (up to 35 %) on data collection and analysis than larger farms (State of Indoor Farming Report 2016, 2016). It may be for this reason that three interviewees, all running farms with fewer than four employees, specified a desire for direction in addition to data presentation. Sophie, who runs a container farm operation that previously used a DST but no longer does, explained this in a discussion about their previous tool and desires for potential features in future tools:

> "I would not say [our previously used tool] was very robust in what it could offer. Again, it was mostly just collecting data and showing it to you. I think anytime you can get more information about that stuff, that's helpful. But it's putting into, "Okay, now that we know the information, what do we need to do about it?" So, I don't know if this new tool would tell us, like, "You need to turn the fan up to this setting," or, you know, those kinds of things. So that would be nice to be able to be told what to do with certain things." – Sophie.

Compatibility

Compatibility refers to characteristics that make the tool consistent with the user's needs, values, or past experiences. Unless a business is built around a specific tool from the outset (which, although uncommon, does occur, such as with container farm owners working with a particular manufacturer), business owners must integrate their DSTs into their existing methods of running their operations. Therefore, if a tool requires a significant amount of change to these methods, the time and effort needed to adapt daily operations to this tool can be a considerable deterrent. In fact, incompatibility with management needs was the most common reason for abandoning a DST amongst survey respondents (64.3 %).

> "I think these tools are very valuable, as long as they don't compromise your business model or make your business model more complex than it needs to be. It's got to be adaptable; it's got to be able to select the bits that you need, and throw out the bits that really don't work for your particular process." – Arthur.

Generally, farmers would prefer a new tool to function with the type of data and physical equipment they already have available. For example, if a tool requires data that necessitates purchasing and installing a large number of new sensors or manually calculating or converting data before inputting it into the tool, this can lead to additional monetary and time costs that become more of a hindrance to users. Additionally, farmers would like new tools to be compatible with other tools they may already be using, such as those that integrate with accounting services. Two interviewees mentioned specific struggles with their current DSTs not integrating with QuickBooks, where being unable to migrate data from QuickBooks to their management DST resulted in wasted time from having to double-input data into both tools, although only one of these interviewees had completely dropped their tool due to this issue. Larger operations typically had more than one DST to cover multiple areas of management. Still, all expressed a desire for these tools or functions to be more smoothly integrated.

> "The tools we use aren't seamless. [We want a tool] where, like, we plug in a sales forecast or our sales from our ERP, and it's just popping out what we need to do. That's what I think we want to get to. We definitely want to get there. Right now, there's definitely a lot of manual intervention and checks, and there's usually like a weekly meeting to kind of align on what that looks like." – Neil.

> "[For our ideal tool] I think it would have all the same capabilities [as our current tools], they would just be embedded. So, the ability to track inventory, ordering, invoicing, customer relations, management, production volume, all of those things are pretty relevant. It's mostly about getting all that to tie together properly." – Rory.

All in all, farmers sought tools tailored to their specific needs and business plans. 23 % of survey respondents who currently use a DST use self-made tools, which allow customization to their needs from the ground up. Among them, 43 % had tried and abandoned a commercial tool before creating their own. Interviewees emphasized the importance of this specificity to their operations; however, developing a tool in-house requires a significant amount of time, energy, and resources, which not all operations can afford to spare.

When it came to commercial tools, a certain balance was required between general usability and specific functionality. Onlythree3 commercial DSTs were used by two or more survey respondents: Artemis (5), Farmhand (3), and AgSquared (2). While these tools were helpful in farms that operated under the assumptions made by these tools, farmers with diverging strategies identified problems with these tools. For example, Arthur stopped using a commercial CEA-specific tool due to its belief that the farm would only need to track and sell individual plants. However, the farm sold loose-leaf lettuce rather than heads, so they needed information about poundage, which the tool could not account for. Instead, the farm switched to a general business management tool. While not explicitly designed for the agricultural world, they found this tool to be more beneficial for their operations due to its greater customization capabilities.

> "It's something that is inherently adaptable. There are some things, silly things. It uses the terminology that is used commonly in the manufacturing industry, like 'manufacturing order,' or 'bill of materials,' or some of these concepts that take a few weeks to get comfortable with. But in principle, it's just the same as if we were making office chairs." – Arthur.

In fact, where a commercially available tool specific to their operational strategies does not already exist, and where operators do not have the time or resources to create their own tool from scratch, operators prefer general but adaptable tools over tools that are specific but difficult to modify. When asked to describe their ideal tools, several interviewees requested more general tools over specific ones, as anything too niche would be of limited use to only certain types of CEA farmers.

> "I think that most people tend to think of just what their farm needs and not how every farm needs it done. And I think that's maybe where some issues come from with tools that exist, is like companies build tools for one type of system. Looking at it from more of a global scale, like, how can we make a single tool that applies to as many of the things as possible? It might not be all of them. But it's gonna benefit a wider group of people in a more specific way." – Sadie.

However, additional problems can arise if the DST is too general and does not allow sufficient flexibility. With the variety of techniques and methods in the CEA world, some interviewees preferred starting with a general tool that can be customized to their specific needs. Farmers sought the ability to customize not only their growing methods and business structure, but also the type of data outputs and recommendations they could receive from the tool. Beyond the specifics of their system type, not every farmer cared about all available data; instead, they had differing priorities based on their business type and current challenges.

> "The process is my process… It's not a one-size-fits-all. So if a new tool was able to kind of have a template and then customize it to certain operations, or certain practices or crops that you're growing, I feel like that would be really helpful and people would be less hesitant. Everybody has sales and customers that they want to keep track of, orders, invoices, expenses, employees, tasks that they're doing, making sure that everything is done the right way. But there's little intricacies of those things or sometimes you have crop waste and crop failure that's not necessarily accounted for. So there's a lot of details, and little things that vary from farm to farm." – John.

> "For indoor agriculture, it has to be like such a well-developed tool. But it would have to be something that encompasses all of the operational, all of the administrative, all the different pieces in one with the opportunity to almost self-create. What are my priorities of what information I need to be accessing quickly and as easily as possible, and then that telling me okay, what information do I need to put in to get that out? Almost like a variable equation that I get to choose how it's spitting out the data to me." – Sadie.

Some interviewees also expressed concerns about value-related compatibility. While several interviewees discussed the benefits of a fully autonomous farm, Ray explained that they would never want to eliminate human labor, due to their beliefs about the importance of human involvement in agriculture. Other interviewees also questioned how widespread adoption could perpetuate issues related to cultural detachment from the Earth and the food we eat. One interviewee, who runs a non-profit farm, also considered the motivation of a tool's creators, noting a struggle to trust tools from companies that do not share specific values. Three interviewees said that they needed to trust the creators of the tools, knowing that the information and technology come from a credible and trustworthy source.

> "We've certainly had offers from time to time… And it turns out people are trying to give things to influencer-type organizations or something that they hope will proselytize for their product so that people will buy it. So, you know, we need it to be something very cheap or free from a like B Corp-type organization that is out there not just to make a buck, but out there to actually enact some beneficial change for the world. Because that's the kind of organizations we end up working with anyway." – Ellis

Complexity

Complexity describes how easy the tool is to understand or use. New DSTs must be user-friendly and reliable to increase adoption. 36 % of survey respondents who had abandoned a previous tool cited difficulty of use as a primary reason. However, when the tool is easy to use, interviewees expressed high gratitude for it from both managers and general staff, as it may reduce the time and mental effort required to complete specific tasks. A tool that can be used just as easily by general staff and more specialized positions allows seamless management and communication between team members.

> "From the front-end point of view, it's very easy to use. And the staff love it. It's easy for them to enter data and reflect the completion of certain steps, tasks." – Arthur.

> "Me being from a manager standpoint, I would like it to be user friendly enough that I'm not the only one that can figure out how to use it, that I can rely on other people that I'm in charge of to be able to use it." – Emmett.

However, the required ease of use can vary depending on how the tool is used within the farm. Neil, who manages a plant factory operation with over 100 employees, noted that while a tool meant for the operators should be "simple to use" and "not easy to mess up" due to the quick nature of daily operations, they would be more understanding if a planning tool used by a manager at their desk were more complicated and slower to use. Many also noted that they do not use all the features of their tools. Sometimes, this is because they do not need all the data or features available; others are deterred by the complexities and learning curve of certain features. They acknowledged that while certain intricate features may make management easier in the long run, they did not have the time currently to set them up.

> "There's still things with this new [tool] that we have, there's things that it can do that we're not using—one, because just to take the time to learn it. And, you know, I have kids. We all have lives." – Emmett.

Abbey, whose farm does not currently use any tools, noted that one of the reasons they have not adopted any is due to the time it would take to incorporate and learn to use them. Being a farm with a small team, they could not afford to have someone take time away from their daily tasks to complete this. However, this is not a barrier for all farms, as this can vary based on available resources, margin sizes, and differing priorities. Sophie, whose farm also does not use any tools, noted that the learning curve would likely not deter them from adopting a tool, citing an acceptance of the longer time required to acclimate to new strategies but a high "willingness to learn new things."

As discussed earlier, there is a desire for customization of these tools. However, if the alteration process is overly complex, farms would need to hire a consultant or a new employee dedicated to the task. At this point, cost again becomes the limiting factor to adoption or optimal use of the tool. If the tool is general enough that its use would only be improved with customization abilities, this may not completely deter use. However, if making any changes (such as correcting data input mistakes) requires support team assistance or a dedicated employee, this becomes a greater problem.

> "I think one of the things I dislike to some extent [about our tool is in] certain areas, when you input something it's kind of stuck in there… Initially, we didn't have as much control, and it was an improper input. Just the amount of work to go and fix that is pretty high. And there's no need for that. Because obviously there's a cost to that, and also there's the lead time. We might be pressing to want it done tomorrow, but if we can't do that ourselves, we're at the mercy of their consultant or their team to get it done. So in the ideal tool, it could do all those things, and you can do most of the adjustments or whatnot in-house, or can learn to do that in-house." – Neil

Insufficient presentation of information can also deter users who lack the time to parse through data. As noted by Connor, who runs a large plant factory operation, sometimes decisions must be made quickly, and there's often "not a lot of time for analysis and pondering." Many farmers need the tool's output information presented in an easy-to-understand manner that can be used immediately to make decisions without further assessment.

Trialability and observability

Trialability describes how the tool can be experimented with before making a full commitment, and Observability describes if or how the user can see results. Trialability and Observability were both cited as necessary for trust in DSTs. Forty-two-point nine percent of survey respondents stated they were likely to adopt a new tool if they had seen it used by others and heard good things about it. However, some interviewees also desired quantifiable demonstrations of a tool's ability to improve their operations, as well as trial periods to test this in their own farm before commitment. When asked how concerns for adoption could be eased when adopting a new tool, 78.6 % ($n = 11$) and 57.1 % ($n = 8$) of interviewees proposed attributes related to observability and trialability, respectively. All non-DST users mentioned trialability as necessary for adoption.

Interviewees sought demonstrations and historical data on the tool's accuracy and its ability to save time and money for operators. Furthermore, six interviewees would need a trial period to feel secure with a tool. Some wanted to conduct formal experiments to verify the results of the provided demonstrations or test if their farm could achieve the same results, while others wanted to observe if management improved, if costs or time spent on specific tasks were reduced, or simply if they felt less stressed using the tool versus not. During these trial periods, if the tool made suggestions for operational decisions, users would want to ensure that these align with the decisions they would make if given the time to sit down and assess the same data.

> "I guess it would depend on those first months or that first year of like, 'Oh, is this the same decision I would have made?' Or you know, sometimes I would maybe follow it and sometimes like I wouldn't to see how things turned out. If it turned out that it actually was offering suggestions that were working and successful, then like yeah, great, that's less I have to worry about." – Ellis

> "I'd probably question at first the suggested problems and related solves. I wouldn't just blindly say, 'Oh, yeah, that's exactly right,' and 'Oh, yeah, now because this app said that this is what's going on, I'm gonna make these changes.' Because I feel like at my core, I would probably question the validity in the app's suggestions… Until maybe I used it a few times and it proved to be right, or just based on my own experience, like I corroborated what it was saying." – Kira

Two interviewees emphasized the importance of trialing new techniques on small sections of the farm to test their effectiveness without risking a full harvest, then incrementally increasing the application to avoid or account for unexpected system-wide impacts. For this reason, as well as to reduce the likelihood of outlier results, some farmers suggested trial period lengths ranging from one month to three complete crop cycles. However, farmers noted that they would continue to test and verify information and decisions beyond this period. Some also wanted the chance to discuss the tool's features and uses with a representative of the tool's producers before adoption. Multiple individuals felt most comfortable if the tool included a warranty and customer support service.

DST desired features

In the interviews, farmers were also asked to describe their ideal DST. This section highlights the features of DSTs that interviewees expressed the most interest in and can assist DST developers in choosing features to focus on for their tools.

Table 4 summarizes suggested features and capabilities for new tools, including desired improvements to their own tools. This table also notes features that interviewees currently have and discussed liking during the interviews, thus would likely be desired in any new tools as well, even if not directly mentioned in the "ideal tool" description. When asked to describe their perfect tool, some interviewees chose to depict every feature they would want, while others only discussed features their current tool lacks; thus, the "total" accounts for overlap between both groups. Numbers in this table should not be interpreted as a definitive count of all interviewees who want or have a certain feature, but rather as an indication of which features were on users' minds. For example, while only one interviewee discussed their tool's existing dashboard view, four others currently use commercial tools advertised to have this feature. Since these four did not express their opinions on dashboards, we cannot determine whether they would want this feature in a future tool or not. Therefore, they were not included in the count for that feature.

As mentioned earlier, the primary limiting factor for adoption amongst interviewees was cost. Though most expressed willingness to adopt a more expensive DST if they knew the monetary benefits would outweigh those costs, Ellis, who runs a non-profit and thus has different financial needs than for-profit operations, would only be willing to adopt it if the tool were free. Others expressed an expectation of a fee but a preference for it to be free.

Daily production features

Multiple interviewees currently have tools with production planning features, including crop and labor scheduling. However, while some could automatically generate a schedule based on desired yields, harvest dates, or orders, others were more manual, and interviewees desired tools that required less effort. One manager, who has multiple farmers growing individually in a shared space, also wanted the ability for individuals to schedule work times visible to others who use the space.

Table 4
Digital decision-support tool (DST) features mentioned by interviewees as either being desired in their ideal DST or as features within their current tool(s) that they use and like.

Category	Feature/Requirement	Description	Interviewees mentioned wanting		Interviewees mentioned having		Total	
			n	(%)	*n*	(%)	*n*	(%)
Labor and Scheduling	Production planning	Seeding, transplant, and harvest scheduling assistance based on inputted harvest dates or orders	2	14 %	7	50 %	9	64 %
	Employee timesheets	Employee hours ("clocked in/out") are trackable within the tool	0	0 %	2	14 %	2	14 %
	Tracking labor tasks	Ability to assign and track daily labor tasks for completion	1	7 %	4	29 %	4	29 %
	Data sharing between employees	Data and notes are shareable between employees on different devices in real-time	0	0 %	5	36 %	5	36 %
Tracking and Monitoring	Plant Tracking/ Barcoding	Tracking crop stage or location within the farm through manual progress notes within the tool or a semi-automated barcoding system	2	14 %	4	29 %	4	29 %
	Environmental Monitoring	Sensor data from environmental conditions are presented within the tool	6	43 %	5	36 %	8	57 %
	Notifications	Alerts for system errors or abnormal environmental conditions are sent to operators' phones or email	1	7 %	4	29 %	4	29 %
	Robotics	Robotics is suggested for easier seeding, transplanting, or harvesting	2	14 %	0	0 %	2	14 %
Automation, Modeling, and Controls	Automated environmental controls	Changing set environmental conditions based on pre-set schedules, or in response to external factors or system errors	3	21 %	1	7 %	4	29 %
	Off-site controls	Manual ability to change environmental or reservoir conditions off-site	1	7 %	1	7 %	2	14 %
	AI Integration	AI is suggested for improved yield prediction, scenario simulations, suggesting management changes, or identifying issues through imaging	6	43 %	0	0 %	6	43 %
	Predictions or simulations	Using models to predict or simulate crop yield, energy or resource use, and/or profit based on current or theoretical conditions and decisions	4	29 %	3	21 %	5	36 %
Interface	Phone or tablet app	Available for mobile iOS or Android devices	3	21 %	3	21 %	5	36 %
	Desktop	Available to use on desktop computers	1	7 %	1	7 %	2	14 %
	Dashboard view	Prioritized information presented together in an easy-to-digest manner at the tool's opening	3	21 %	1	7 %	4	29 %
Other Support	Integration with financial management	Tools include, consider, or integrate with other tools focused on the stages before and/or after crop production, such as incoming orders, inventory management, supply costs, and/or sales revenue	5	36 %	4	29 %	7	50 %
	References	Space within the tool for training modules, important documents, notes, or FAQ sections	2	14 %	2	14 %	4	29 %
	Tech support team	Access to a customer service or technical support team to troubleshoot problems with the tool	0	0 %	3	21 %	3	21 %

Though no interviewees requested the inclusion of timesheets or trackable daily labor tasks in their ideal tool, multiple interviewees commended these abilities in their existing tools. Similarly, data sharing between team members, including notes and up-to-date task lists, was noted by current DST users as advantageous for communication. Several interviewees also manually notated and tracked plants using their tools; however, a barcoding system was described as the more desirable method for plant tracking.

While most farms had sensors, only 5 discussed the sensor data being presented together in a tool to easily facilitate frequent environmental monitoring, as described in 35 % of interviewees' "ideal tool." Two specifically wanted "measured, on-point, real-time data coming to you live" (as described by container farmer Hugo), which their current tools did not provide. Others wanted more environmental conditions monitored. Currently collected data varied by farm, but generally included temperature, relative humidity, CO_2 concentration, plant weight, and water reservoir pH, EC, and temperature. Two interviewees would like more information on heat distribution in their farms, and another would like to have more temperature sensors and cameras throughout their farm. Monitoring features were significant to farmers, as the data could not only be used to identify areas requiring immediate attention but could also be analyzed to determine environmental optimization based on historical conditions and harvests.

Another advantage of real-time monitoring is the potential to receive notifications or alerts. Multiple interviewees already receive these notifications either through an app, text, or email when important equipment, such as pumps, shuts down or when conditions, such as nutrient or pH levels, are off. A few farmers also requested or currently have off-site controls, meaning the ability to change specific environmental settings remotely via an app, which can provide immediate relief from issues they may be alerted to. However, farmers want notifications as early as possible in potential emergencies.

> "That's probably the biggest thing is like, you need alarms on stuff not to tell you when something's gonna go wrong, but before something's gone wrong. Before it hits a dramatic situation, you need an alarm, that if 10 is the dramatic situation, you want it to hit at 5 or 6 so that you can catch it early enough." – Emmett.

Modeling and AI integration

Collected data can also be fed into predictive models or simulations. Interviewees requesting such specifically wanted to make yield predictions based on the data they already monitor (namely, temperature, humidity, light schedules, reservoir pH, and EC) and historical data on plant weight and sizes under past conditions, so that they might find the optimal nutrients and climate for their crop or group of crops. One farmer also sought to use forecasting for demand planning to predict the percentage of lettuce heads that will be healthy and large enough to sell, and use this information for seed-related decisions. 36 % of interviewees also discussed how microclimates in their farms, caused by non-uniform airflow and temperature distributions, presented challenges to their yield and crop health. They expressed a desire for tools to either account for variances in predictions or help identify strategies to minimize non-uniformity.

While some already incorporate modeling or forecasting into their DST, the speed and accuracy of these predictions could be improved through the integration of AI, as requested by multiple interviewees. Data collection can also be used to train AI for various purposes, although the quality and quantity of data obtained significantly impact the accuracy of the results. Though some operations are sitting on a "goldmine" of data, as described by greenhouse manager Emmett, not all of that data is being tracked or recorded in many operations. In this study, although some farms that did not use "formal" DSTs or consider data in decision-making still collected data through sensors (thus have some capability to train AI models), they may not achieve sufficient accuracy due to the type or amount of data collected. For example, according to the IUNU's (2023) State of CEA Report, farms with the most accurate yield predictions are those that measure total harvest weight, rather than using sample weights, which is more common amongst farms due to labor constraints (2023 State of CEA, 2023).

Interviewees expressed mixed opinions on using AI in their management tools; however, the variance mostly pertained to the capacity in which it would be used. No interviewees declared they wouldn't use it, but while some described their ideal farm as fully automated, others wanted continued human involvement. According to the interviewees, AI was suggested for multiple purposes. Beyond modeling improvement, farmers were also interested in using these models to explore scenarios that personally interested them, such as switching their seeds to a different brand or receiving suggestions for improvements based on current conditions. Some would like this as a plug-and-play tool, where you can input settings to decide on (such as water schedules, irrigation, lighting, seed choice, and temperature) and receive answers on how best to approach the situation for increased yield or reduced costs. Others envisioned a scenario where an AI functions similarly to a human employee, noticing when conditions appear off during regular operations and quickly suggesting changes based on prior data and experiences.

Another suggested use for AI was with robotics. Two interviewees envisioned farms operating similarly to manufacturing factories and wanted machines that could plant and harvest simultaneously. However, as discussed earlier, this would not align with the goals and beliefs of all farmers. Sadie, who owns a container farm operated by only themself and volunteers, also proposed a voice-based method to activate controls or prompt simulation runs, envisioning a chatbot or virtual assistant system similar to ChatGPT (ChatGPT, San Francisco, CA) or Siri (Apple, Cupertino, CA).

> "I would love to just have a personal assistant. Yeah, like, who can sit there and do all these things while I'm just like saying it to them. I think if it was actually, like, a tool that was built out for me, it would be that human… Being able to communicate in a way that I actually communicate without having to fill my head with data and numbers all the time, because that burns me out." – Sadie

AI and imaging were discussed together repeatedly as a method to identify pests and crop health issues, in the vein of existing crop disease identification apps such as Plantix (Berlin, Germany)) or Agrio (Tel Aviv, Israel), which are designed primarily around outdoor crops and household ornamental plants. No interviewees currently use such apps; instead, they requested apps with a focus on issues common to their crops, either using the typical photo-taking app method or a rolling imaging machine that can scan through all the crops to search for problems. One interviewee suggested integration with decision suggestions and controls based on identified issues. For example, if the imaging software detected a nitrogen deficiency in the crop, John, a microgreens grower, wanted the system to automatically add nitrogen to the water reservoir to correct the issue.

Four interviewees specifically wanted the decisions suggested by AI to be automatically implemented with controls, such as adjusting CO_2 concentration, lighting, humidity, temperature, and water chemistry, or purchasing different seeds based on explored cost scenarios. For example, if crops appear unhealthy and the AI suspects a nitrogen deficiency as the problem, the system could automatically add nitrogen to the reservoir. Therefore, there would be less time and mental bandwidth spent on making and implementing these decisions, allowing managers to focus on decision-making elsewhere.

However, as many are hesitant to fully trust the technology, including farmers who are asking for AI-based automation, most noted that human involvement would be essential. This could include the ability to override changes the system wants to implement based on an app notification. However, most users wanted this in the form of asking for confirmation (or double confirmation) before implementing changes, especially when making purchases or adjusting schedules. Still, one interviewee noted that while they would like AI-based suggestions, they would never want automated changes; they would only want recommendations. As discussed in Section 3.2.4, users are more likely to accept suggested changes after sufficiently long trial periods, during which they can confirm the accuracy and alignment with their own decision-making.

Interface and training

As aligned with the discussion in Section 3.2.2. and 3.2.3. Multiple interviewees highlighted the ease of use and customizability of a tool's interface as important factors in encouraging its use. Farmers preferred dashboard views that could present relevant information in a clear, concise, and easy-to-understand manner. The ability to visualize data was noted as essential for some farmers to understand the "story of the crop experience," as Connor described. However, as not all farms had the same concerns, Sadie requested high customizability of the dashboard view, giving farmers the ability to self-create priorities and select which information they want on demand, thereby reducing further time spent on assessments.

Preferences for phone/tablet apps versus desktop software were not discussed extensively in the interviews but rather tended to depend on the roles of the decision-makers. Those with managerial positions who have time to sit in the office may prefer desktops, while daily operators working mainly on the farm like the mobility of a phone or tablet app. A tool with both desktop and app functionality was suggested as ideal due to its flexibility. One farmer, Sadie, noted that accessibility tools, such as AI-based voice controls, could add a layer of assistance.

Regarding employee training for new tools, 74.1 % of survey respondents preferred a combination of online and in-person training, while 21.4 % preferred online training only, and 4.8 % preferred in-person training only. Farmers discussed the online option as easier for self-paced learning, as well as training new staff. Jason, whose farm's mission focused on employment, rehabilitation, and community improvement, also saw the DST as a learning opportunity and educational tool, and thus wanted sufficient training included to help the user fully understand how the farm is run. Similarly, John envisioned accessible training modules that would allow employees to easily relearn forgotten processes or tasks, available in both written and video demonstration forms, to accommodate different learning styles.

Multiple interviewees also requested that a document manager or similar section be included within the DST, where notes and important documents, such as standard operating procedures, can be easily referenced. Two envisioned a tool with an FAQ or problem-tracking section, where suggested solutions to common problems can be referenced, or where operators (or, in the case of AI-based problem detection, the software directly) can track issues as they occur and note how they were resolved for easier resolution and trend identification in the future.

> "If you could like take a photo of your problem, and it's almost like a questionnaire… and it spit out potential solves… Then almost get tracked over time, like if you've had this problem before, because I swear, one reoccurring issue we have is like our seeds have gone bad or there was a problem with the seed from the company and it sometimes manifests differently… We can usually relate it back to the seeds, the seed quality, but we didn't really catch on to that trend until it happened at least 20 times, I swear, over the last five years." – Kira.

Decision-support system integration

The farmers also wanted new tools that could be easily integrated into their business model. This was particularly demonstrated in discussions related to the flow of information through the different stages of the business. This flow of data, in the case of a CEA operation, is represented in Fig. 2. Five interviewees discussed the need for this flow to be better accounted for in their tools, particularly regarding financial data integration.

Financial data is threaded on both the front and back end of the production stage. For one, current finances and orders often guide the

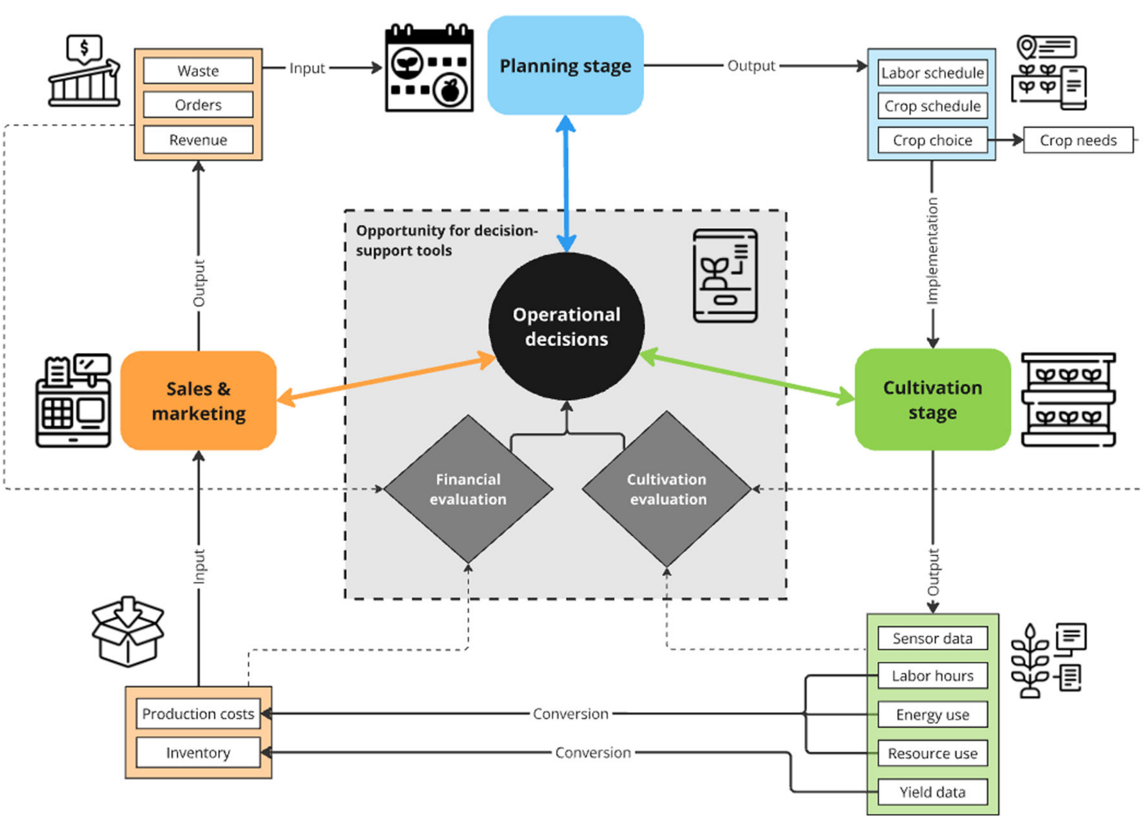

Fig. 2. Simplistic demonstration of the data flow through the different stages of CEA operations.

planning stage, particularly in terms of which crops are grown, when, and in what volume. Second, the harvest data becomes fulfilled orders or available products to sell, which translates to revenue (or waste if unsold). This data needs to be pushed both to the next stage in the supply chain and into a feedback loop for the next planning stage. As such, several interviewees expressed a desire for invoicing, ordering supplies, creating and updating orders, tracking inventory, and identifying discrepancies between consumer orders and available harvest as a semi-automated process embedded in a DST. In particular, the concept of a live inventory available for viewing at harvest by either managers or consumers came up in three interviews. This integration can save valuable time and effort.

> "A lot of our time has been spent on my end as the operations manager, ordering supplies, prepping inventory, making changes to planting schedules… Then the side of our sales and marketing manager, a lot of his time is spent blending orders, updating orders, finding issues and, you know, the harvesting, and making sure all those things are aligned. If we had something to semi-automate this it would give us a lot more room for him to start developing, you know, more robust social media marketing plans, or for me to start researching pieces of automation to improve our production efficiency. So, enabling us to do more with fewer people." – Rory.

However, some would also like this data to be easily transferable in and out to financial-specific software. Three interviewees, including one who does not use any production-related tools, specifically requested integrability with QuickBooks, which is used by 39 % of CEA operators according to one industry report (State of Indoor Farming 2020, 2020). Most interviewees already had financial management tools in some capacity; however, these were often separate and not easily integrated with their production tools, or lacked additional desirable features, such as live inventory. There was an overall trend among users to desire a single tool that met all their management needs, as simply as possible. However, users also expressed hesitancy to shift away from their current tools or methods, which already work well for them, due to the time and effort required to switch, even if these tools are more limited in capabilities.

John, who owns a container farm company, mentioned the ease of management that would result from building a company around a DST rather than the other way around. However, depending on the operation's available resources at conception, this is not always practical, and is out of the question for already existing companies. However, as growing companies benefit from economies of scale, switching to a single, all-encompassing, farm-specific tool becomes not only more manageable but a logical next step. Neil, one of the largest farms interviewed, explained how they already had tools for every aspect of management needed, but were now facing challenges with clunky and non-seamless data transfer between them all. Thus, their next goal for their farm is to combine these features into a single tool and explore how they can be used together with machine learning to enhance data-driven decision-making further.

> "[My ideal tool would] be a combination of AI and manual… It would be taking in all of our data, so everything from climate control… maybe the mean downtime of certain systems, lighting, climate, yield data, QA data, and it could kind of build out. And also thinking like, sales forecasts, or like throughput, if we plant 100 plants… how much are we actually going to get in a box at the end of the day that aren't going to be too small or have any type of issues? So take all of that in, and then it can really demand plan for us based on that data would be like, the ultimate tool. Obviously, there's still the manual side to double check data, make sure it's clean coming in But over time it would learn as well and see those kind of one-offs that might happen… So you can kind of figure out those extremes… I think that's very much within the realm of what's available today. It's just feeding it great data." – Neil.

This description meets that of a digital twin. A digital twin (DT) is a virtual representation of a process or item (the "physical twin"—in this case, the farm) utilizing predictive models continuously updated with monitored data to predict future conditions. This would involve combining historical data, live monitoring, crop modeling, and artificial intelligence to represent the farming environment fully, predict yield and other metrics such as energy or resource use, and inform decisions on operational management. As a rapidly emerging concept, DTs have been utilized to increase energy efficiency in fields such as manufacturing, automation, and built environments; however, the complex interactions between living and non-living elements in agricultural systems have left this industry comparatively behind in terms of DT technology (Pylianidis et al., 2021). Nonetheless, DTs have been conceptualized and prototyped for various forms of CEA, including greenhouses and plant factories (Ahmed et al., 2019; Anthony Howard et al., 2020; Chaux et al., 2021; Ghandar et al., 2021; González et al., 2022; Jans-Singh et al., 2020; Mengi et al., 2024; Purcell et al., 2023; Zhang et al., 2023).

Discussion

Despite strong interest in digital decision support tools (DSTs), 48.4 % of current or past users reported abandoning at least one tool, often due to incompatibility (64 %) or insufficient perceived benefits (57 %), consistent with prior research on technology discontinuance (Rogers & Williams, 1983). These findings highlight that even early adopters in CEA prioritize relative advantage and compatibility when evaluating DSTs.

Insights from farmer interviews and surveys inform a framework for enhancing DST design, structured around the five Diffusion of Innovation (DOI) attributes—relative advantage, compatibility, complexity, trialability, and observability—offering actionable guidance for developers ahead of stakeholder-specific recommendations.

To enhance relative advantage, DSTs should improve profitability through enhanced yield, quality, food safety, and labor efficiency, while remaining cost-effective. While this study did not assess specific pricing strategies, the 2020 State of Indoor Farming report revealed a wide range of user preferences: 44 % preferred white-glove service, 36 % preferred free software with paid support, and 20 % wanted an entirely free, self-service option (State of Indoor Farming 2020, 2020). Developers must tailor pricing models such as subscription-based, freemium, or bundled to diverse user preferences, as cost remains the top barrier to adoption.

Reliability and sustained support are crucial for the adoption of DST. One farmer (Ellis) raised these issues directly, and recent industry developments underscore the fears. In 2023, Farmhand was the second-most used tool among survey participants. Yet in April 2025, Freight Farm, the parent company, filed for bankruptcy, and the tool was shut down without a transition plan ("Freight Farms Files for Chapter 7 Bankruptcy," 2025). Though users received some support from the broader farming community, the tool's abrupt termination left many feeling abandoned (Francis, 2025). The sudden shutdown of Farmhand in 2023, despite its popularity, highlights the importance of developers establishing transparent contingency plans to maintain user trust and operational stability.

Enhancing compatibility requires aligning DSTs with already existing data formats, technologies, business models, and workflows. Developers should engage end-users during the design lifecycle to ensure relevance across varied CEA operations and prioritize interoperability. In particular, smaller farms requested greater interoperability between production-focused DSTs and financial or inventory tracking software. Meanwhile, larger operations often use multiple DSTs simultaneously, indicating a need for seamless integration between tools to maximize cumulative impact.

Integrated DSTs can yield synergistic benefits, akin to "technology multipliers," in supply chain optimization (Stamer et al., 2024) or the compounded effects of coordinated sustainability policies. by enabling adaptive, data-driven decisions across farm systems. (Wu, 2025) suggests that DST adoption depends not only on the attributes of individual tools, but also on how tools interact within a farm's broader digital ecosystem. For instance, real-time temperature and humidity data from one system can be directly fed into crop scheduling software, enabling adaptive plans that reduce energy use and optimize. Developers should design tools that complement broader digital ecosystems to maximize value and adoption.

Users value DSTs that strike a balance between simplicity and customization, enabling tailored dashboards, metrics, and workflows for diverse farm models. Intuitive interfaces, clear training resources, and strong support services are essential to reduce complexity and encourage sustained use. For example, farms that sell via farmers' markets may have different data needs than those managing staggered deliveries to multiple retailers. Customization increases the tool's applicability across diverse farm models. Simultaneously, developers should prioritize intuitive user interfaces, well-organized training materials, and responsive customer support to reduce barriers to initial and sustained use

To improve trialability, developers are encouraged to offer trial periods long enough to cover at least one complete crop cycle, ideally ranging from one to three months. This allows farmers to evaluate functionality within the unique rhythms of their operations. To enhance observability, developers can provide demonstrations, use case examples, peer testimonials, and scientific validation of tool outputs. These not only improve understanding of what the tool can achieve but also build user trust before purchase or commitment.

Practical implications

This research found that most CEA farmers have entered the decision phase of DST adoption. Even non-users were generally aware of DSTs and held favorable views, with decisions to reject tools often tied to perceived disadvantages, cost, or a mismatch in scale. While some users discontinued tool use after implementation, this was usually due to issues of incompatibility or limited relative advantage, aligning with DOI-based expectations for rejection discontinuance. Additionally, some non-users felt unable to adopt DSTs due to limitations related to their operational scale and financial resources. Past literature suggests that for these users, who can be considered late adopters or laggards, trialability may be particularly important, as it is more relevant to the decision-making phase. Special focus on increasing or demonstrating compatibility and relative advantages may also encourage continuation through the implementation phase (Rogers & Williams, 1983).

To maximize adoption and long-term use of DSTs in the CEA sector, the following implications should be considered for developers, tool users, and policymakers.

a. Implications for Developers

Survey and interview data suggest that DST adoption is not the primary barrier; instead, retention and continued use are. Developers should pay close attention to compatibility, relative advantage, complexity, and observability, as these traits significantly influence both adoption and discontinuance decisions. To support design processes, we propose the following guiding questions for developers:

1. Cost: Is the price aligned with expected user returns?
2. Performance: Does it save time, reduce costs, or improve product quality?
3. Ease of Use: Is the interface intuitive and user-friendly?
4. Time Requirement: Are data inputs minimal, and are outputs easy to interpret?
5. System Compatibility: Does it work with current sensors, data formats, and internet connectivity?
6. Tool Compatibility: Does it integrate with other software (e.g., accounting)?
7. Relevance: Does it solve actual user problems?
8. Trial Periods: Can users test the tool risk-free?
9. Demonstrations: Are case studies, demo videos, or peer testimonials available?
10. Training and Support: Is onboarding easy, and is help available?
11. Customization: Can users tailor it to their unique workflows?
12. Reliability: Can users trust its long-term stability and continued support?
13. Communication: Are users included in feedback and update cycles?

Customization can improve compatibility and decrease perceived complexity. For instance, small farms selling directly to consumers may have very different scheduling needs than B2B suppliers with variable harvest dates. DSTs that allow flexible dashboard and feature configuration will better serve this diverse sector.

Moreover, the integration of DSTs may result in synergistic value. Interviewees from larger farms reported using multiple tools in tandem, such as combining real-time sensor data with production planning systems, to optimize decisions. This aligns with the concept of the "technology multiplier," where the whole is greater than the sum of its parts. Developers should consider interoperability not just as an add-on, but as a core feature of their systems.

The lifespan and reliability of tools must also be addressed transparently. The unexpected shutdown of Farmhand (Freight Farm, Boston, MA) in 2025 left users without support, despite its widespread use just two years earlier. Building trust through contingency planning, data export options, and transparent support policies will increase resilience and reduce user skepticism.

b. Implications for Tool Users and Farmers

Farmers play a crucial role in shaping the development of tools. This study found that even non-users expressed interest in DSTs, meaning barriers are often practical rather than ideological. Farmers should be encouraged to:

1. Participate in co-design feedback loops with developers.
2. Trial DSTs and share preferences to improve tool alignment.
3. Advocate for modularity, integration, and affordability in vendor relationships.

Many smaller-scale growers in this study expressed a desire for DSTs that work across multiple management areas (e.g., environmental monitoring and financial planning) yet are flexible and affordable. Tool selection should be aligned with system complexity, growth stage, and data literacy.

c. Implications for Policymakers and Funders

Public support can play a critical role in expanding digital agriculture. Policymakers should consider:

1. Subsidies or tax credits for DST implementation, especially for small to mid-scale farms.
2. Interoperability standards that encourage integration across platforms.
3. Digital training programs tailored for CEA operators, many of whom may be newer to agriculture but are more tech-forward.

With CEA emerging as a key piece of urban and resilient food systems, investment in trusted, well-supported DSTs will help the sector scale efficiently and sustainably.

Theoretical contributions

This study represents the first known application of the DOI framework to the CEA sector. While technology adoption in traditional agricultural contexts has been widely studied with DOI and other theoretical frameworks, CEA differs in several critical ways, including its high level of technological integration and relative novelty. This paper applies and extends DOI to digital DSTs in CEA. By linking DOI attributes to design recommendations, this research also bridges the gap between theoretical constructs and practical guidance within the CEA field for developers, illustrating how innovation characteristics can be operationalized to enhance adoptability.

Additionally, although our research did not focus on individual-level barriers, the interviews revealed certain discrepancies in farmers' perceptions of DSTs compared to existing literature in traditional agriculture. For example, previous studies have noted that DSTs that prescribe operational changes are often rejected by traditional farmers due to their preference for acting as the primary decision-makers (McCown, 2002). Conversely, though not universal, most interviews in this study indicated that CEA farmers would prefer automated decision-making (after a trial period to verify the tool's accuracy). In fact, Sophie, one of the four interviewees who had not adopted any DSTs, specifically explained that she would not see a purpose in adopting DSTs that do not at least offer direction, indicating that preferences for self-reliance may not be as influential on adoption. Similarly, all 14 interviewees expressed overall positive attitudes towards digital DSTs as a whole, regardless of their personal use of them. At the same time, past literature finds that negative community perceptions of DSTs may be a prevalent barrier to adoption in traditional sectors (Thomas et al., 2023). This could relate to why some attributes appeared to be more commonplace than in similar studies in conventional agriculture. For example, trialability and observability were recurring themes, with most interviewees citing these as essential factors in their decisions to adopt the technology. This contrasts with literature in traditional agriculture Ranjan et al. (2022), which concluded neither of these attributes was a recurring theme, as well as the fact that, according to one review of precision agriculture DSTs in conventional agriculture, only two papers had assessed these attributes, in comparison to relative advantage, which was discussed in 30 (Pathak et al., 2019). These results suggest that the relative importance of DOI attributes in the high-technology domain of CEA may differ from traditional agricultural settings, prompting future research to consider context-specific weighting of adoption factors.

There may also be implications for segmentation within CEA as well as between CEA and traditional agriculture. Furthermore, the findings presented in the previous paper in this series (Lindow et al., 2025) revealed that the age of the operators themselves was not clearly correlated with adoption. However, the operators' total years of agricultural experience may be. The GH industry as a whole is also further into its maturity than PFs or CFs (Shamshiri et al., 2018), as reflected in the survey responses, which showed that the majority of operations were over 5 years old and involved GHs. However, while reactions indicated that the youngest operations were the most likely to currently use DSTs (and the oldest group, 10+ years old, were least likely to use any), the youngest operations were also twice as likely to have previously tried but abandoned a DST than the oldest operations.

In contrast, GHs were both the least likely to use DSTs among the system types and the most likely to have tried but abandoned a previous tool. These differing trends suggest that the lower adoption rate in GHs cannot be attributed solely to its maturity. This implies that market segmentation may exist not only between CEA and traditional agriculture, but also within the CEA industry itself, with operational age and prior experience in traditional agriculture as potential modifying factors in decision-making for DST adoption.

Finally, this work contributes to the broader literature on innovation and knowledge transfer by illustrating how established theories such as DOI can be adapted to emerging, highly digitalized agricultural contexts. To further ground our work in the journal's discourse, we draw from Ali et al. (2022), who empirically examine organizational-level IT innovation adoption in multiple contexts using structural equation modeling. Their findings on organizational readiness, culture, and technology infrastructure align with ours, strengthening the connection between our study and the Journal of Innovation & Knowledge Research on innovation adoption. Our findings also support recent calls in this journal for research that integrates theory with actionable guidance for practitioners and policymakers (Rejeb et al., 2023). By demonstrating that specific DOI attributes (e.g., trialability, observability) may hold different weights in technologically advanced agricultural systems, this study highlights the importance of context-specific theoretical adaptation, a key issue central to JIK's mission of advancing both scholarly and practical knowledge on innovation.

Limitations and future research directions

This research identified differing adoption rates among various CEA systems and operational ages, as well as indications of varying acceptance of DSTs among CEA farmers compared to traditional farmers. Further research on individual-level acceptance and attitudes in CEA, such as using TPB or TAM frameworks, could help to interrogate these findings further and identify more specific adopter groups within CEA, thereby guiding better marketing strategies tailored to these groups.

This mixed-methods study provides a foundation for understanding the barriers and requirements of digital DST adoption amongst CEA operators. However, by its design, this study was not comprehensive. As demonstrated in Schmeitz (2023), which assessed the adoption of a specific service software for CEA farmers in Mexico, Morocco, and the Netherlands, barriers to technology adoption vary by market. Location, technological development, and culture all influence the need for adoption support. All survey respondents and interviewees from our study were based in the United States; thus, the results can only be applied to the US market.

Additionally, the referral sample technique and online searches for qualified farms may have missed operations without websites; therefore, CEA farms without an online presence were underrepresented in the results. Response bias may also have occurred due to the selection of respondents. Busier operations may not have responded due to difficulties in time management; however, operations struggling with time management would also be a relevant group to question regarding DST experience. There is also an underrepresentation of cannabis growers, who, though not the focus of this study, are still a part of the CEA industry and were still reached out to in the survey search. Only one cannabis grower responded to the survey, likely due to the higher privacy of the industry due to legality-related stigmas.

This study employs a quantitative approach to data collection through survey responses, as well as a qualitative assessment through interviews. While the interviews were able to further expand on the survey results, some interviewees naturally discussed specific topics in greater depth than others. For example, as addressed in Section 3.3, while some interviewees described every detail they could think of that they wanted in a DST, others spoke only of features they hadn't seen or experienced themselves. Thus, these results may underreport appreciation for useful but standard tool features. A secondary quantitative study could be conducted to better account for this, such as by asking a new group of survey respondents to select desired/relevant features or barriers from lists generated based on the interviews, which could verify how well-aligned the interview findings are with the larger population captured by the survey.

Additionally, one question on the survey asked respondents to self-report their willingness to adopt new technology. However, how users perceive themselves as adopting may not align with their actual practices (Burton, 2004), and this topic was not thoroughly explored in the interviews. Further studies could be conducted to more accurately assess the behaviors and patterns of CEA operators when it comes to adopting technology.

As cost was identified as a barrier to adoption, future research may explore different payment and subscription models to examine users' willingness to adopt or continue using them. This type of research may also be explored in markets outside of the United States. Additionally, this study identifies features and qualities of interest for CEA operators but does not explore how to portray best or market tools with these features to operators. Future research may focus not only on the DST characteristics that users desire, but also on how to most effectively support the adoption of these tools from a marketing standpoint.

Conclusion

We surveyed 44 CEA operators across the United States and interviewed 14 respondents for in-depth opinions based on their experiences, preferences, and concerns regarding the adoption of DSTs. From these interviews, we used the DOI Theory framework to identify characteristics of DSTs in CEA that prevent and encourage adoption. This research contributes to existing literature on CEA and innovation theory by applying DOI to the field for the first time and by identifying key differentiations between CEA and traditional agriculture adoption trends, which both point towards the importance of contextual analysis in innovation research as well as the relevance of market segmentation between these different technologies and systems. In addition to identifying features and capabilities that CEA operators want to see in their future tools, we also provided direct recommendations for questions that DST developers should consider throughout the design, using the characteristics of DOI as discussed throughout the interviews. This research will help guide DST developers in creating tools that not only achieve higher adoption rates but also provide the most effective assistance to operators who adopt them.

Based on these findings, future industry development should consider how DSTs can be designed with compatibility in mind, including advancement in data integration, and by fostering interoperability between complementary DSTs. Doing so may exploit the synergistic effects of effective interoperability among DSTs, which can not only encourage adoption but also increase the relative advantages of each tool in combination. Encouraging data standardization would also enhance compatibility between systems, particularly between sensor and monitoring operational DSTs and financial management tools. Future research should consider adopter-level attitudes, beliefs, and values, which, in combination with the present innovation-level assessment, will provide a more comprehensive picture of the innovation-adopter relationships to better guide tool development and marketing.

CRediT authorship contribution statement

Lauren Lindow: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Catherine Campbell:** Writing – review & editing, Supervision, Software, Conceptualization. **Coleman Longwater:** Software, Formal analysis. **Ying Zhang:** Writing – review & editing, Supervision. **Ana Martin-Ryals:** Writing – review & editing. **Ziynet Boz:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Funding acquisition, Conceptualization.

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