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# Evaluating the adoption of sensor and robotic technologies from a multi-stakeholder perspective: The case of greenhouse sector in China

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ABSTRACT

Emerging digital technologies are transforming greenhouse production, yet it remains unclear which technologies are likely to achieve widespread adoption. This study evaluates greenhouse sensor and robotic technologies from an innovation-oriented perspective, aiming to bridge the gap between technology assessment and innovation adoption. Using the Diffusion of Innovation theory as a framework, we defined evaluation criteria based on the perceived technology attributes. Our evaluation process involved multiple stakeholder groups within the Chinese greenhouse sector—growers, investors, technology suppliers, and policy makers. The Bayesian best-worst method was used to elicit stakeholder preferences and expert-rated technology scores for each attribute. These were combined to produce a probabilistic overall performance score for each technology. The results highlighted the heterogeneous preferences among stakeholders. The leaf temperature sensor received the highest score among growers and policy makers. Investors and technology suppliers favored the scouting and harvesting robots, respectively. These findings underscore the importance of tailoring technology promotion strategies to the specific priorities of each stakeholder group.

## 1. Introduction

The agricultural sector is currently undergoing a rapid transition towards increased digitalisation and automation (King, 2017; Saiz-Rubio and Rovira-Más, 2020; Verdouw et al., 2021). This shift is commonly referred to as smart farming (Regan, 2019; Verdouw et al., 2021), digital farming (Shamshiri et al., 2018), and agriculture 5.0 (Saiz-Rubio and Rovira-Más, 2020). At the core of this transformation are several key technologies: (i) sensors and the Internet of Things for data collection, (ii) data platforms and cloud management for data storage and analytics, (iii) artificial intelligence for advanced planning and optimisation, and (iv) automation technologies for replacing human labor and executing physical tasks (Ehlers et al., 2022; Shamshiri et al., 2018).

This transition digitalisation and automation is particularly evident in greenhouse production systems, which, due to their relatively closed environments, are ideally suited for the integration of these advanced technologies (Verdouw et al., 2014). Recent technological innovations in horticulture have led to the development of sensors that directly monitor the status of plants such as sap flow and leaf photosynthesis (van Straten et al., 2010). In addition, robotics for leaf removal (Van Henten et al., 2006), targeted spraying for pest control (Dai et al., 2022; Sammons et al., 2005), and harvesting (Bac et al., 2014) have shown promise in preliminary cases.

Currently, these technologies are in the early market introduction phase (Bac et al., 2014; Gil et al., 2023; Hemming, 2020), where it will be determined whether they can reach "critical mass" adoption (Rogers, 1995) and diffuse more widely into the market. The aim of this study is to identify which technologies are likely to achieve widespread adoption in the future. To this end, the study examines the priorities of various stakeholder groups regarding the perceived technology attributes (i.e., cost-benefit, environmental impact, trialability, observability, complexity, and compatibility) that influence technology adoption, as well as the performance of each technology on these attributes. The following research questions are formulated:

1. What is the relative importance of different technology attributes from the perspective of different stakeholder groups?
2. What is the relative performance of technologies on these attributes?

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3. Which technologies have the highest likelihood of achieving widespread adoption?

The rest of the paper is organized as follows: Section 2 first describes the research context, including a literature review. Section 3 presents the evaluation framework and the elicitation method. Section 4 outlines the survey procedures. Section 5 discusses the results of stakeholder preferences and technology performance on the attributes defined in the DOI, along with the ranking of technologies. The paper ends with conclusions and discussion.

## 2. Research context

This section provides a literature review and research context.

### 2.1. Gap between technology assessment and innovation studies

Several studies have evaluated digital and automation agricultural technologies based on their functionality and performance in fulfilling specific tasks. For example, Bac et al. (2017) evaluated the performance of a sweet pepper harvesting robot using 13 technical indicators, such as grasp success, cut success, and stem damage rate. Kutyrev et al. (2022) used expert judgement to assess a horticultural robotic platform using 18 effectiveness criteria. Balafoutis et al. (2020) examined the economic, environmental, and labor impacts, as well as the adoption readiness of 1064 smart farming technologies projects, drawing from scientific papers, research projects, and industrial products.

A potential limitation in these assessments is the weak role of adopter preferences in the evaluation process. Technology assessment studies typically focus on the functionality of a technology, while the priorities of its users remain largely invisible (McCampbell et al., 2023). However, technologies should be evaluated not only on their performance against technical criteria, but also on the extent to which these criteria align with the value of potential adopters (de Oca Munguia and Llewellyn, 2020; Geisler, 2002). Rogers' diffusion of innovation (DOI) theory provides a framework for broadening the scope of technology assessment to include the perspective of technology users (Aizstrauta et al., 2015).

According to DOI theory, it is not only the characteristics of the innovation itself, but rather the adopters' perceptions of its technological attributes that significantly influence its adoption 0/0/0000 0:00:00 AM. The five perceived attributes—relative advantage, compatibility, complexity, trialability, and observability—collectively explain 49 to 87 % of the variance in the rate of adoption of an innovation (Rogers, 1995). These attributes provide a general framework to describe innovations in universal terms.

**Table 1**
Summary of selected literature on the evaluation or adoption of agricultural technologies.

| Authors | Scope | Methods | Metrics/theoretical framework | Stakeholders/evaluator |
|---|---|---|---|---|
| Bac et al. (2017) | Evaluate the technical performance of a harvesting robot for sweet pepper. | On-site experiments | 13 indicators on technical performance defined by authors | Authors |
| Balafoutis et al. (2020) | Assess the economic, environmental, and labor impact, as well as adoption readiness of smart farming technologies. | Literature review; survey | Diffusion of innovation; 26 performance indicators on economics, environment, and labor aspects discussed in the literature | Technology providers, authors synthesize information from literature and research projects |
| (Kutyrev et al., 2022) | Assess the effectiveness of robotic platform for horticulture. | Expert interview | 18 criteria on effectiveness of robot | Technical experts |
| Cagnetti and Braccini (2023) | Understand the enablers, barriers, and outcomes of business information systems adoption in Italian agriculture. | Survey; chi-square analysis | Enablers and barriers indicators defined in literature | Agricultural companies |
| von Veltheim and Heise (2020) | Investigate user ex ante acceptance of field robots from the perspective of technology experts in Europe. | Semi-structured interview | Technology acceptance model | Technology experts |
| Mir and Padma (2020) | Identify contextual and critical factors influencing agricultural decision support systems among Indian farmers. | Survey; regression analysis; reliability and multi co-linearity tests | Technology acceptance model; Technology-Organization-Environment model; Human Organization Technology-fit framework | Farmers, extensionist |
| Caffaro et al. (2020) | Identify factors driving intention to adopt smart farming technologies among Indian farmers. | Survey; structural equation modelling | Technology acceptance model; diffusion of innovation theory | Farmers |
| Mohr and Kühl (2021) | Identify factors influencing the acceptance of AI systems in agriculture in Germany. | Survey; structural equation modelling | Technology acceptance model | Farmers and university members (who work on farms) |
| Giua et al. (2022) | Investigate intention to use and the actual adoption of smart farming technologies. | Survey; structural equation modelling; Zero-Inflated Poisson Regression | Unified Theory of Acceptance and Use of Technology | Farmers |
| Rose and Bhattacharya (2023) | Identify factors influencing UK growers' intention to adopt autonomous robots | Survey; qualitative interview | 9 factors discussed in literature (cost/benefit; infrastructure; robot performance; repair and maintenance; skills; trust; safety; security; and technology readiness) | Farmers |
| Gil et al. (2023) | Explain the low adoption of agricultural robotics in European farms | Budget estimation; (qualitative) case study | Cost/benefit, business models | Authors |
| Tamirat et al. (2023) | Elicit expectations and concerns of several stakeholder groups regarding use of robots in field crop operations | Survey; interview | Economic, social and environmental indicators identified from the literature | Farmers, robot companies, researchers, project site managers, public authorities, environmental organizations |
| Michels et al. (2024) | Understand German farmers' intention to buy alternative fuel tractors | Survey; structural equation modelling | Unified Theory of Acceptance and Use of Technology | Farmers |
| Wang et al. (2024) | Explore the motivation factors for end-users to accept intelligent agricultural decision-making in China | Survey; structural equation modelling | (Extended) technology acceptance model | Farmers |
| Michaliszyn-Gabryś et al. (2024) | Understand the impact of the introduction of laser weed control system on markets and agricultural practices in the context of sustainability. | Social life cycle assessment; focus group interview | Three pillars of sustainability | Farmers, business representatives, NGOs and public administration |

While extensive literature exists on agricultural innovation adoption and diffusion, much of it focuses on the characteristics of adopters, their social networks, and the general farming context, while less emphasis on the attributes of the technologies themselves (Shang et al., 2021). Most studies investigate the facilitator and barriers of adoption, as summarized in Table 1. However, there is lack of research that integrates both the relative importance stakeholders assign to the factors influencing technology adoption and how technologies perform on these factors.

### 2.2. Inclusion of a broader range of stakeholders

Innovation is a co-evolution process that involves a lot of feedback, with various actors playing roles at different levels (Smits and Den Hertog, 2007). Stakeholders often speak different languages and draw on diverse expertise when assessing technologies (Tavella, 2016). During the innovation diffusion process, they seek to create and share information through interpersonal communication channels to achieve mutual understanding. In practice, however, stakeholders often have varying or even conflicting perspectives concerning on the benefits and risks of introducing a technology, emphasizing different values and pursing different economic, social and environmental goals (Tavella, 2016). For example, a study found that farmers are mainly concerned about the investment cost, safety, reliability and adaptability of robots, while non-farmers emphasize environmental impacts and the co-design of solutions (Tamirat et al., 2023). This highlights the need to extend the focus beyond just technology adopters and consider a broader range of stakeholders in technology assessments (Alcon et al., 2014; Moretti et al., 2023; Yazdani et al., 2023).

Despite the importance of this broader inclusion, there is little understanding about how to effectively integrate stakeholders with different concerns, interests, values into the technology assessment process (Burgess and Chilvers, 2006; White and Bourne, 2007). Existing studies targeted mostly on farmers while undermined other key stakeholders (Osrof et al., 2023), and only a few integrated perspectives from multiple stakeholder groups (e.g., Michaliszyn-Gabryś et al., 2024; Tamirat et al., 2023). To facilitate a multi-stakeholder dialogue, our goal is to understand stakeholders' priorities and map out their relationships and levels of influence the technology diffusion process (Kajimbwa and Mhanga, 2022). The major stakeholders in China's greenhouse sector include growers, investors, technology suppliers, and policy makers. Below we outline the roles and influence of each stakeholder group.

In China, ***growers*** are primarily involved in management activities and do not have ownership of the greenhouse units. Their responsibilities include analyzing data produced by sensors and climate computers, optimizing the greenhouse environment, conducting regular crop scouting and registration, and making cultivation decisions such as de-leafing, harvesting, and crop protection. Growers' goal is to increase greenhouse production and achieve higher economic returns. Growers are the end-user of greenhouse technologies. An innovation will diffuse only if information about its use-value characteristics is transmitted to the potential users (Lundvall, 2016). Growers could also act as modifiers, designers, and opponents of innovative technologies, and thus have a significant influence on the diffusion process of greenhouse technologies (Oudshoorn and Pinch, 2003).

Due to the high investment costs, high-tech greenhouse ***investors*** in China are usually run by agricultural companies, rather than households. Many of the high-tech greenhouse companies in China do not have an agricultural background but instead come from the real estate, construction, or information technology sectors (Wang et al., 2023). These investors typically do not directly participate in the day-to-day management of greenhouse operations. Instead, they serve as funds providers and owners of the greenhouse assets. As purchasers of greenhouse technologies, their role is to invest in and acquire these technologies rather than directly managing their implementation.

Greenhouse horticulture is a supplier-dominated sector, where research and development (R&D) is mainly performed and diffused by ***technology suppliers*** and public-funded research and extension services (Berkers and Geels, 2011; Pavitt, 1984). Private agricultural R&D investment has grown rapidly since 2000 (Hu et al., 2011). Beyond selling products, technology suppliers also provide training and post-installation technical support. They maintain close contact with both investors and growers, closely monitor the implementation of their products and collecting feedback from growers on their experiences. When problems occur, growers often turn to technology suppliers for solutions.

Finally, ***policy makers*** play a crucial role in the greenhouse sector in various ways. This includes regional officers from the regional Ministry of Agriculture and Rural Affairs (MOA), regional agricultural extension officers, as well as universities and research institutions. MOA officers are responsible for coordinating regional agricultural development plans and budget allocations. In addition, they sometimes act as joint investors of greenhouse projects in China through state-owned enterprises established by local governments (Gong and Huang, 2016). Extension officers are responsible for the provision of extension services and technology demonstrations to farmers (Zhong et al., 2020). Universities and research institutions serve as primary sources of agricultural innovation and can steer the direction of R&D in the agricultural sector in China (Hu et al., 2011).

This paper addresses the gap between technology assessment and innovation studies by proposing a quantitative evaluation procedure that combines multiple stakeholders' preferences with expert judgements to assess early-stage digital and automation agricultural technologies from an innovation-oriented, forward-looking perspective. Our research contributes to both technology assessment and innovation studies by demonstrating how Rogers' DOI theory can serve as an overarching framework in technology evaluation. Furthermore, it illustrates how multiple stakeholders' preferences and expert opinions can be integrated into a unified evaluation framework. The procedure is flexible enough to be applied to the evaluation of technologies beyond digital agricultural technologies.

## 3. Methods

In the Methods section, we first present the evaluation framework. Subsections 3.2 and 3.3 introduce the best-worst method and the Bayesian best-worst method, followed by a discussion of the consistency of the judgements. Subsection 3.5 provides a step-by-step explanation of how the technology alternatives were scored and ranked.

### 3.1. Evaluation framework

In the evaluation framework, we aim to link the technology and stakeholder dimensions. The evaluation framework consists of two stages (see Fig. 1).

The first stage is the elicitation of the relative importance of the attributes of technologies from four groups of stakeholders: growers, investors, technology suppliers, and policy makers. In the second stage, technical experts were employed to elicit the performance score of technology on the identified attributes.

The evaluation framework defines the evaluation criteria based on the Diffusion of Innovation of Rogers (1962), a widely adopted theory in agricultural innovation adoption studies. DOI identified five perceived attributes of an innovation: relative advantage, *complexity*, *compatibility*, *trialability*, and *observability*, as important explanations of adoption. In this evaluation framework, relative advantage is decomposed into *cost-benefit* and *environmental impacts*. Cost-benefit is further decomposed into three sub-criteria: *initial investment*, cost *reduction*, and *revenue increase*. An overview of the description for each evaluation criterion is shown in Table 2.

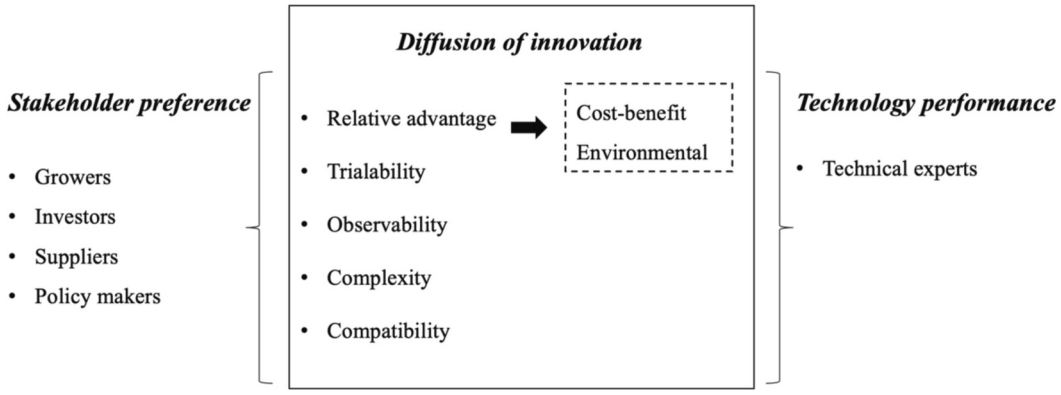



**Fig. 1.** Evaluation framework.

**Table 2**
Description of the evaluation criteria situated for greenhouse production.

| Criteria | Description |
|---|---|
| Cost-benefit ($c_1$) | The initial investment to obtain the technology, the reduction in operational costs, and the increase in revenue as a result of using the technology. |
| Initial investment ($c_{11}$) | The initial costs or outlay of the investment to obtain the technology. |
| Cost reduction ($c_{12}$) | The reduction in yearly operation costs or expenditures as a result of using the technology. |
| Revenue increase ($c_{13}$) | The increase in revenue (through an increase in yield or quality) as a result of using the technology. |
| Environmental impacts ($c_2$) | The ability of the technology to reduce negative environmental impacts (greenhouse gas/carbon emissions and chemical residues) generated from the greenhouse production process. |
| Trialability ($c_3$) | The ease with which the technology can be tested and tried on a small scale in the greenhouse before having to decide to adopt it. |
| Observability ($c_4$) | The benefits or results of using the technology are tangible, have social visibility, they can be observed, imagined, and perceived by myself and others. |
| Complexity ($c_5$) | The level of difficulty to understand, learn, and use the technology. |
| Compatibility ($c_6$) | How well the technology fits well the existing greenhouse physical infrastructure and the established work routine, practices, and management platform. |

### 3.2. Technologies to be evaluated

The evaluated technologies are sap flow sensor, leaf temperature sensor, deleafing robot, harvesting robot, and scouting robot. A description of the functionalities of the technologies is given in Table 3. As these technologies are still at the trail stage and there is little knowledge and commercial application of these technologies, experts were consulted on their performance.

**Table 3**
Description of the evaluated greenhouse technologies.

| Technology | Function |
|---|---|
| Sap flow sensor ($t_1$) | Monitoring plant water consumption, which can reflect water deficit or over-irrigation of plant status. |
| Leaf temperature sensor ($t_2$) | Providing real-time data on the surface temperature of plant leaves to avoid overheating or unwanted cooling. |
| Deleafing robot ($t_3$) | Detecting leaf petioles and cutting the old leaves. |
| Harvesting robot ($t_4$) | Localizing and determining the ripeness of fruit; griping and detaching ripe fruit and transport of a detached fruit. |
| Scouting robot ($t_5$) | Detecting pests and diseases, mapping defects caused by pests, and counting flowers and fruits. |

### 3.3. Best-worst method

There are several methods for weights elicitation in a multicriteria decision-making (MCDM) problem. The best-worst method (BWM), developed by Rezaei (2015), has been receiving increasing application. BWM uses pairwise comparisons for weighting. BWM uses pairwise comparisons for weighting. In BWM, a decision maker (DM) first identifies the best and worst criteria, then compares each of the other criteria with both the best and worst criteria. In total, $2n-3$ comparisons are evaluated by the DM for a problem with $n$ criteria.

Unlike single vector methods such as the simple multi-attribute rating technique (SMART) (Edwards, 1977) and the Swing method (Von Winterfeldt and Edwards, 1986), BWM has two opposite anchors in its procedure, which can produce results that are less prone to anchoring bias (Rezaei et al., 2024). Compared to full matrix methods such as the analytical hierarchy process (AHP) (Saaty, 1977) and the analytical network process (ANP) (Saaty, 1996), BWM has the advantage of having higher data efficiency and less cognitive burden on the respondents, and thus higher consistency (Rezaei, 2015). As BWM uses ratio scales, it also suffers less from equalizing bias compared to methods that directly assign importance to attributes (Rezaei et al., 2022).

The procedure of BWM can be summarized in five steps:

*Step 1.* Determine a set of decision criteria $C = \{c_1, c_2, \ldots, c_n\}$.

*Step 2.* Identify the best (most important) $c_B$ and the worst (least important) criteria $c_W$.

*Step 3.* Determine the preference of the best criterion $B$ over all the other criteria using a number between 1 and 9 (1: equally important, 9: extremely more important). The resulting Best-to-Others vector would be:

$$A_B = (a_{B1}, a_{B2}, \ldots, a_{Bn}) \tag{1}$$

where $a_{Bj}$ indicates the preference of the best criterion $B$ over criterion $j$, with $a_{BB} = 1$.

*Step 4.* Determine the preference of all the other criteria over the worst criterion $W$ using a number between 1 and 9. This results in the Others-to-Worst vector

$$A_W = (a_{1W}, a_{2W}, \ldots, a_{nW})^T \tag{2}$$

where $a_{jw}$ indicates the preference of criterion $j$ over the worst criterion $W$, with $a_{WW} = 1$.

*Step 5.* Calculate the optimal weights $(w_1^*, w_2^*, \ldots, w_n^*)$. The optimal weights are derived by solving the following model (3):

$$\min \xi \tag{3}$$

$$\text{s.t. } \sum_j w_j = 1$$
$$\left|w_B/w_j - a_{Bj}\right| \le \xi, \text{ for all } j$$
$$\left|w_j/w_W - a_{jW}\right| \le \xi, \text{ for all } j$$

Solving the above problem gives the optimal weights $(w_1^*, w_2^*, \ldots, w_n^*)$ and $\xi^*$.

### 3.4. Consistency of judgements

To evaluate whether the judgements are reliable, the consistency of the decision-maker's judgement needs to be evaluated. Consistency in pairwise comparisons can be divided into two categories: cardinal consistency and ordinal consistency (Siraj et al., 2015). We checked the consistency of judgements by calculating both the original consistency ratio proposed by Rezaei (2015) and an input-based consistency ratio proposed by Liang et al. (2020).

The original consistency ratio $CR^O$ is an output-based consistency measure, defined as:

$$CR^O = \xi^* / \text{consistency index} \tag{4}$$

where $\xi^*$ is the optimal objective value of Eq. (3) and the consistency index is a value that depends on the value of $a_{BW}$ (Table 4). The range of is $CR^O$ is $[0, 1]$. The lower the consistency ratio, the higher the reliability of the result.

The original output-based consistency ratio only considers cardinal consistency and fails to account for ordinal consistency. Therefore, we also evaluated each DM's judgements using the input-based consistency ratio. The input-based consistency ratio can indicate a DM's consistency level based on its pairwise comparison matrix directly.

Eqs. (5) and (6) show the input-based consistency ratio $CR^I$ for BWM pairwise-comparisons.

$$CR^I = \max_j CR_j^I \tag{5}$$

where

$$CR_j^I = \begin{cases} \left|a_{Bj} \times a_{jW} - a_{BW}\right| / \left(a_{BW} \times a_{BW} - a_{BW}\right) & a_{BW} > 1 \\ 0 & a_{BW} = 1 \end{cases} \tag{6}$$

$CR^I$ is the global input-based consistency ratio for all criteria. $CR_j^I$ represents the local consistency level associated with criterion $C_j$. The consistency thresholds (maximum acceptable $CR^I$) for combinations that range from 3 to 9 criteria with highest evaluation grades from 3 to 9 is shown in Table 5.

### 3.5. Bayesian best-worst method

BWM can calculate a weight vector for one DM at a time. When multiple DMs are present, a single weight vector for the group is often obtained by aggregating individual priorities using, for example, the arithmetic or geometric mean (Ishizaka and Labib, 2011). However, this way of aggregation is sensitive to outliers. If one DM has different weights from the entire group, the aggregated group weights will be significantly influenced.

Moreover, the information on the dispersion of DM's preference is also lost due to the aggregation (Mohammadi and Rezaei, 2020). In group MCDM problems, a criterion is ranked as more important than another merely if its group (weighted) average weight is higher than another. However, this way of determining the ranking of criteria does not reveal the confidence of the importance relationship between each pair of criteria.

The nature of the underlying problem is a group decision-making problem. Facing the preferences of a group of DMs, we want to develop a deeper understanding of the confidence of importance of criteria among stakeholders. In 2019, Mohammadi and Rezaei (2020) proposed the Bayesian Best-Worst method (Bayesian BWM). The inputs of the Bayesian BWM are the same as those of the original BWM. The difference is that the Bayesian BWM assumes the optimal group weights as a probability distribution, rather than a precise weight vector. The notion of credal ranking was introduced to describe the degree to which one criterion is more important than one another.

The Bayesian BWM meaningfully views the multicriteria group DM problem from a probabilistic perspective. The criteria are seen as random events, and the weights are their likelihoods of occurrence. For probabilistic reasoning, all the inputs and outputs of the Bayesian BWM are modeled as probability distributions. The inputs of the $k^{th}$ DM of the BWM, the Best-to-Others vector $A_B^k$ and the Others-to-Worst vector $A_W^k$, are modeled as multinomial distributions:

$$A_W^k | w^k \sim multinomial\left(w^k\right), \forall k = 1, \ldots, K \tag{7}$$

$$A_B^k | w^k \sim multinomial\left(1/w^k\right), \forall k = 1, \ldots, K \tag{8}$$

The weight vector $w$ is modeled as the Dirichlet distribution, which satisfies the non-negativity and sum-to-one properties. The Dirichlet distribution is a conjugate prior of the multinomial distribution, which means that the posterior distribution would also be a Dirichlet distribution:

$$Dir(w^{agg} | \alpha) = 1/B(\alpha) \prod_{j=1}^{n} w_j^{\alpha_j - 1}, \alpha \in \mathbb{R}^n \tag{9}$$

The individual weight vector $w^k$ is expected to be in the proximity of $w^{agg}$:

$$w^k | w^{agg} \sim Dir(\gamma \times w^{agg}), \forall k = 1, \ldots, K \tag{10}$$

where $\gamma$ is a non-negative parameter that governs the closeness between $w^k$ and $w^{agg}$. $\gamma$ follows a gamma distribution:

**Table 4**
Consistency index (CI) table, from Rezaei (2015).

| $a_{BW}$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| CI | 0.00 | 0.44 | 1.00 | 1.63 | 2.30 | 3.00 | 3.73 | 4.47 | 5.23 |

**Table 5**
Thresholds for different combinations using input-based consistency measurement, from Liang et al. (2020).

| | Criteria | | | | | | |
|---|---|---|---|---|---|---|---|
| Scales | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| 3 | 0.1667 | 0.1667 | 0.1667 | 0.1667 | 0.1667 | 0.1667 | 0.1667 |
| 4 | 0.1121 | 0.1529 | 0.1898 | 0.2206 | 0.2527 | 0.2577 | 0.2683 |
| 5 | 0.1354 | 0.1994 | 0.2306 | 0.2546 | 0.2716 | 0.2844 | 0.296 |
| 6 | 0.133 | 0.199 | 0.2643 | 0.3044 | 0.3144 | 0.3221 | 0.3262 |
| 7 | 0.1294 | 0.2457 | 0.2819 | 0.3029 | 0.3144 | 0.3251 | 0.3403 |
| 8 | 0.1309 | 0.2521 | 0.2958 | 0.3154 | 0.3408 | 0.362 | 0.3657 |
| 9 | 0.1359 | 0.2681 | 0.3062 | 0.3337 | 0.3517 | 0.362 | 0.3662 |

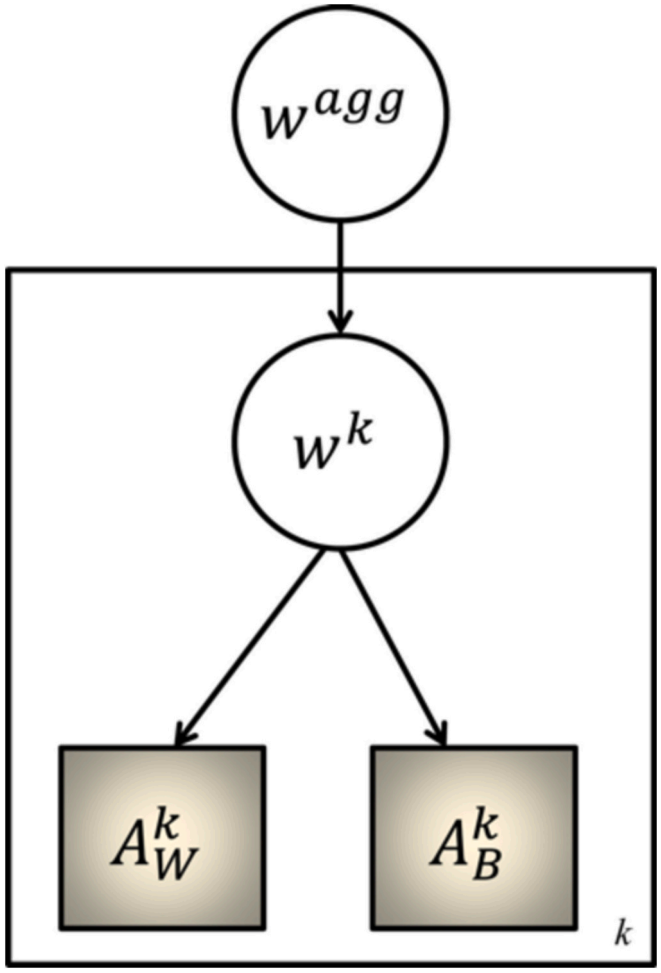



**Fig. 2.** Probabilistic hierarchical model of the Bayesian BWM, from Mohammadi and Rezaei (2020).

$$\gamma \sim gamma(a, b) \tag{11}$$

The values of a and b were set to 0.1, as $gamma(0.1, 0.1)$ is similar to a uniform distribution. Using it as an uninformative prior distribution can avoid biased inference on the posterior distribution.

A Bayesian hierarchical model is proposed to compute the overall weights of the group DM problem (see Fig. 2). The value of the overall group weight vector $w^{agg}$ depends on the weight of individual DM $w^k$; the value of $w^k$ is dependent on $A_B^k$ and $A_W^k$.

The prior distribution of $w^{agg}$ is modeled as an uninformative Dirichlet distribution:

$$w^{agg} \sim Dir(1) \tag{12}$$

The specified Bayesian model does not have a closed-form solution. The posterior distributions can be computed using the Markov-chain Monte Carlo (MCMC) technique (Gilks et al., 1995). The "just another Gibbs sampler" can be used to generate the random sample (Plummer, 2004). The confidence of the importance relations between various criteria (credal ranking) can be calculated based on the approximated posterior distribution of $w^{agg}$. For details on the Bayesian BWM, please refer to the work of Mohammadi and Rezaei (2020). For this study, we used a Bayesian BWM solver (https://bestworstmethod.com/software/) to compute the weight vector of stakeholders and the experts' scores of technologies performance.

### 3.6. Steps of the technology evaluation process

In this subsection, we explain step by step how the rankings and scores of the technologies were obtained. The flowchart of this process is shown in Fig. 3.

*Step 1*. Define evaluation criteria for greenhouse technology ranking.

The first step involved defining the evaluation criteria for ranking greenhouse technologies. Six criteria were determined by the researchers according to the technology attributes defined in the DOI, with the first criterion (*Cost-benefit*) having three sub-criteria, as shown in Table 2. To ensure that these criteria were clearly defined and easily understood, consultations were conducted with professionals and university students specializing in greenhouse horticulture. The criteria and sub-criteria are denoted as:

$$C = \{c_1, c_2, \ldots, c_6\} \tag{13}$$

$$c_1 = \{c_{11}, c_{12}, c_{13}\} \tag{14}$$

*Step 2*. Elicit stakeholder preferences for the evaluation criteria.

A Phase I stakeholder survey was conducted with growers, investors, suppliers, and policy makers. Each stakeholder was asked to identify the most important and least important criteria for adopting or promoting digital greenhouse technologies. They also conducted pairwise comparisons between the criteria following the guidelines of BWM. The Best-to-Others and Other-to-Worst vectors for the $k^{th}$ DM are denoted as:

$$A_B^k = \left(a_{B1}^k, a_{B2}^k, \ldots, a_{B6}^k\right) \tag{15}$$

$$A_W^k = \left(a_{1W}^k, a_{2W}^k, \ldots, a_{6W}^k\right)^T \tag{16}$$

*Step 3*. Calculate the aggregated group stakeholder preferences.

For each stakeholder group, solve the Bayesian BWM model using the above-mentioned Bayesian BWM solver, with $A_B^k$ and $A_W^k$ from all stakeholders in the group serving as inputs. 15,000 MCMC samples of the overall group weight were drawn from the posterior distribution of $w^{agg}$, denoted as:

$$w^{agg} = \left\{w_1^{agg}, w_2^{agg}, w_3^{agg}, w_4^{agg}, w_5^{agg}, w_6^{agg}\right\} \tag{17}$$

$$w_1^{agg} = \left\{w_{11}^{agg}, w_{12}^{agg}, w_{13}^{agg}\right\} \tag{18}$$

Similarly, the relative performance of technologies on criterion $j$ ($s_j^{agg}$) was also elicited using the Bayesian BWM.

*Step 4*. Elicit expert scores for technology performance on each criterion.

In Phase II, an expert survey was conducted with technical experts who have extensive knowledge on these technologies. Each expert was asked to identify the best-performing and worst-performing technology for each criterion. They also conducted pairwise comparisons between technologies for each criterion following the guidelines of BWM. The Best-to-Others and Other-to-Worst vectors of the $k^{th}$ expert for the $j^{th}$ criterion are denoted as:

$$T_B^k = \left(t_{B1}^k, t_{B2}^k, \ldots, t_{B5}^k\right) \tag{19}$$

$$T_W^k = \left(t_{1W}^k, t_{2W}^k, \ldots, t_{5W}^k\right)^T \tag{20}$$

*Step 5*. Calculate the overall group score for technology on each criterion.

For each criterion, the Bayesian BWM model was solved using the Bayesian BWM solver, with $T_B^k$ and $T_W^k$ from all experts serving as inputs. 15,000 MCMC samples of the overall group technology score were drawn from the posterior distribution of $s_j^{agg}$, denoted as:

$$s_j^{agg} = \left\{s_{j1}^{agg}, s_{j2}^{agg}, s_{j3}^{agg}, s_{j4}^{agg}, s_{j5}^{agg}\right\} \tag{21}$$

The technology score on the $m^{th}$ sub-criterion of $C_1$ (*Cost-benefit*) is

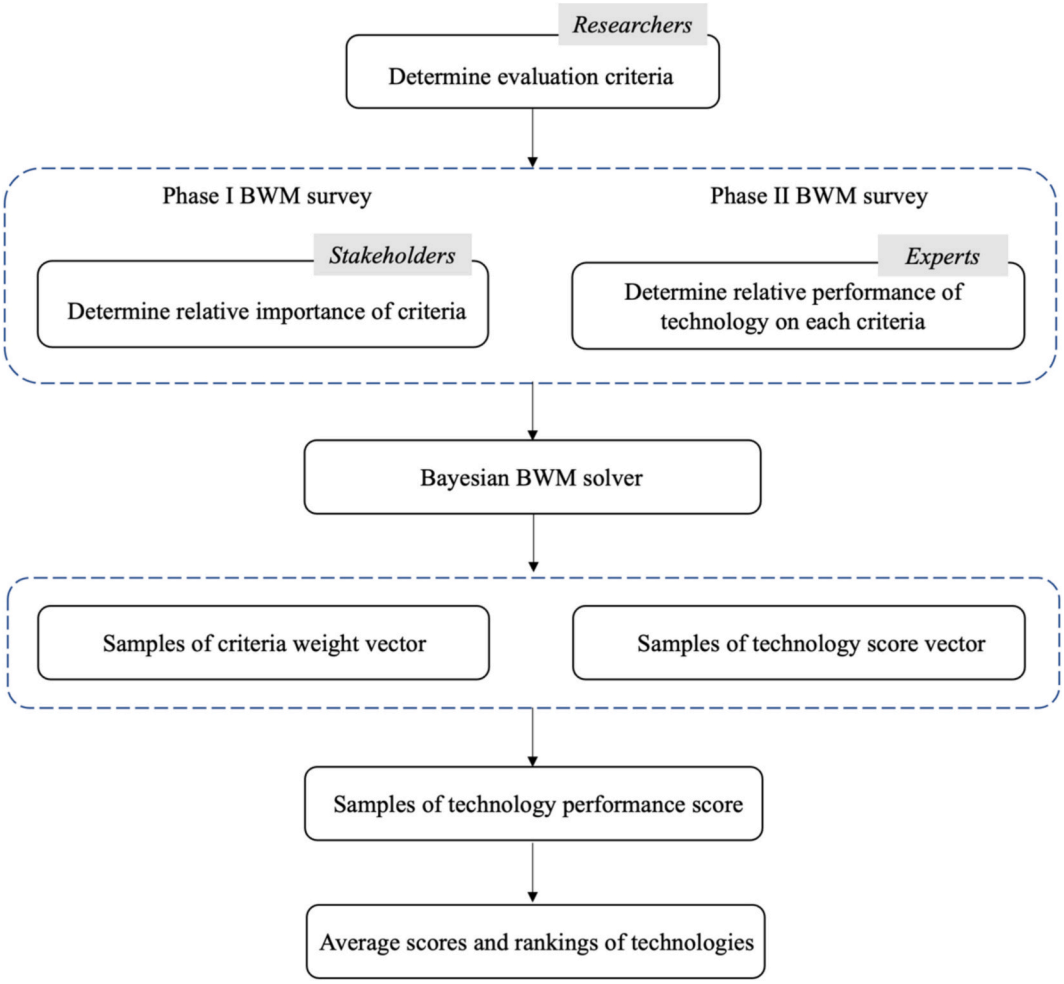



**Fig. 3.** Flowchart of the evaluation and ranking process for technologies.

denoted as:

$$s_{1m}^{agg} = \{s_{1m1}^{agg}, s_{1m2}^{agg}, s_{1m3}^{agg}, s_{1m4}^{agg}, s_{1m5}^{agg}\} \tag{22}$$

*Step 6*. Calculate the overall performance score and credal ranking for each technology.

The performance of technology alternatives can be assessed using a multi-attribute value function, which can be multiplicative, additive, or non-additive. To rank the technologies, we calculated a composite index, referred to as the overall technology performance score ($S$), by combining the sampled stakeholder preferences and expert scores using an additive value function. It should be noted that the additive value function assumes the technology attributes (evaluation criteria) are mutually preferentially independent and difference independent (Liang et al., 2023; Rezaei et al., 2022).

The overall performance score for the $t^{th}$ technology is calculated as:

$$S_t = w_1^{agg} \sum_{m=1}^{3} w_{1m}^{agg} s_{1mt}^{agg} + \sum_{j=2}^{6} w_j^{agg} s_{jt}^{agg} \tag{23}$$

In total, we obtained 15,000 MCMC samples of the overall performance score for each technology. We assume that the technologies achieving higher average overall performance scores are more likely to be widely adopted or promoted during the technology diffusion process.

The concept of credal ranking was first introduced by Mohammadi and Rezaei (2020). Unlike other ranking schemes, credal ranking provides a confidence measure which can calibrate the degree to which one option is superior to one another.

For a pair of technologies $t_i$ and $t_j$, the credal ordering is defined as:

$$O = (t_i, t_j, R, d) \tag{24}$$

where $R$ is the relationship or ranking between the technologies $t_i$ and $t$, i.e., $<$, $>$, or $=$; and $d \in [0, 1]$ represents the confidence of the relation.

With 15,000 samples of the overall performance score of for each technology, the confidence that $t_i$ is superior to $t_j$ is computed as:

$$P(t_i > t_j) = \frac{1}{15000} \sum_{q=1}^{15000} I_{\left(S_{t_i}^q > S_{t_j}^q\right)} \tag{25}$$

where $S_t^q$ is the $q^{th}$ sample of the overall performance score of technology $t$, and $I$ is 1 if the condition in the subscript holds, and 0 otherwise.

Given a set of technologies $T = (t_1, t_2, \ldots, t_n)$, for each pair of technologies, one can compute the confidence that one is superior to one another. The credal ranking is a set of credal orderings which includes all pairs $(t_i, t_j)$, for all $t_i, t_j \in T$. A traditional ranking of technologies can be obtained by applying a threshold of 0.5 to the credal ranking.

## 4. Data collection

In this section, we explain the data collection process from stakeholders and experts, as described in Subsections 4.1 and 4.2 respectively.

### 4.1. Data collection on stakeholders' preferences

We collected data from four groups of stakeholders: greenhouse

growers, private investors, machinery and equipment suppliers, and agricultural policy makers in China. Ten respondents for each group were reached through snowball sampling. The interviewees were asked to provide their functions to verify their eligibility to be qualified respondents. Growers were included only if they were in cultivation management roles, such as setting greenhouse climate strategies, and managing labor, in a modern greenhouse. Investors were general managers or directors in modern greenhouse companies located in Beijing, Shanghai, Shandong, Gansu, Jiangsu, Yunnan, and Guangdong provinces. This sample of growers and investors represents the stakeholders of major modern greenhouse companies in China.

Additional information on age, management experience (in years), greenhouse size, types of crops planted, and educational level was collected from growers. In the sample of growers, almost everyone grows tomatoes, half also planted cucumbers, and a few grow flowers, peppers, or lettuce. Only one grower cultivates hops for beer brewing. The growers range from 30 to 48 years old, with an average age of 36 years. They have been working in the greenhouse sector for 5 to 13 years, managing a greenhouse of 5 to 30 ha. Most of them hold a bachelor's degree or higher.

Machinery and equipment suppliers were technical or marketing specialists from companies that provide equipment such as sensors, climate computers, and screens to greenhouse companies. Policy makers were recruited from the local ministry of agriculture, agricultural research institutes, extension centers, and quasi-commercialized state-owned enterprises. Policy makers were included only if they had participated in the design of local agricultural policy or had been involved in local greenhouse projects.

The Phase I stakeholder survey was designed according to the guidelines of BWM (see supplementary material) and documented in Excel format. The surveys were conducted through a web conferencing platform and presented to the respondents through screen sharing. At the beginning of the survey, a list of greenhouse plant-monitoring sensors and automation technologies and their functions was presented. Each interviewee was asked if they had heard of or worked with these technologies.

Next, an overview of all evaluation criteria was presented, during which the interviewer read out the description of each criterion in Table 2 for the respondent. In the main part of the survey, respondents were asked to indicate which criteria would be the most and least important in a situation where they use (for growers), adopt (for investors), promote (for policy makers), or communicate (for suppliers) a digital or automation technology for greenhouse production. Respondents were then asked to compare the other criteria to the selected most and least important criteria by assigning a number between 1 and 9. The respondents were asked to explain the choices they made throughout the interview. All individual stakeholders' judgements were found to be consistent, whether evaluated using the original output-based consistency ratio proposed by Rezaei (2015) or the input-based consistency ratio proposed by Liang et al. (2020).

The interview ended with a general discussion, where the respondents were invited to share their experiences on using, adopting, communicating, or promoting greenhouse technologies. Each interview lasted 40 to 70 min.

### 4.2. Expert evaluation of technology performance

A second round of interviews was conducted with the technical experts to elicit the score of technologies on a given criteria. The experts were selected to make sure they have knowledge about each technology. Experts from both the academic and the industry were included to make sure that the expertise was complementary. Table 6 shows the background and expertise of the experts.

The Phase II expert survey was also designed according to the BWM guidelines. An example of the questionnaire with experts can be found in supplementary material. As in the previous phase, an overview of all the evaluation criteria was presented, and the researchers read the descriptions to the experts. The technologies were compared across eight dimensions, including three sub-criteria under the first main criterion and the other five main criteria. The experts were then asked to identify which technologies scored best and worst on each criterion or sub-criterion. They were then asked to compare the remaining technologies to the selected best- and worst-performing ones by assigning a number between 1 and 9. Throughout the interview, the experts were encouraged to explain their choices. Each individual expert's judgements were found to be consistent, whether assessed using the original output-based consistency ratio or the input-based consistency ratio.

**Table 6**
Experts' details.

| Expert | Background |
|---|---|
| #1 | Industry. Director of a horticultural consultancy company. |
| #2 | Academia. Senior Scientist, Wageningen University& Research. Experts on crop production, crop physiology, cropping systems, and crop growth models. |
| #3 | Industry. Director of an agricultural robotic company. |
| #4 | Academia. Senior Scientist, Wageningen University& Research. Experts on sensors and detection systems. |

## 5. Results

The findings are organized into three subsections. In Subsection 5.1, we present the elicited preference of stakeholders on the technology attributes (or evaluation criteria). The performance scores of the technologies on each criterion are summarized in Subsection 5.2. Finally, Subsection 5.3 displays the calculated overall performance scores and credal rankings of the technologies.

### 5.1. Stakeholders' heterogeneous preferences on technology attributes

The overall optimal global weights of the six attributes and the local weights of the *cost-benefit* sub-criteria of each stakeholder group are shown in Table 7 and Table 8. While preferences for the technology attributes defined in the DOI vary among stakeholders, *cost-benefit* consistently emerges as the most important criterion for all stakeholder groups. Investors place higher importance on a technology's potential to increase revenue, whereas suppliers prioritize a technology's ability to reduce operating costs. Compared to other stakeholders, policy makers are more concerned with the initial investment costs.

Policy makers rank *environmental impact* as the fourth most important criterion, with a group weight of 0.155. In contrast, growers, investors, and suppliers place less emphasis on this criterion, with weights ranging from 0.108 to 0.110. Policy makers highlighted that existing environmental regulations for greenhouse production, such as prohibition on coal heating and requirements for drain water recycling, are mainly enforced at the initial stages of greenhouse projects. For the other stakeholders, *environmental impact* was the least or the second least important criterion. One investor stated, "If the additional costs of environmentally friendly technologies are not compensated by other entities, *environmental impacts* would be my least concern."

**Table 7**
Overall optimal global weights and their rankings (in brackets) of the six main criteria by stakeholder group.

| Criteria | Growers | Investors | Suppliers | Policy makers |
|---|---|---|---|---|
| $C_1$ Cost-benefit | 0.308 (1) | 0.314 (1) | 0.319 (1) | 0.292 (1) |
| $C_2$ Environment | 0.108 (5) | 0.110 (6) | 0.110 (6) | 0.155 (4) |
| $C_3$ Trialability | 0.176 (2) | 0.128 (4) | 0.112 (5) | 0.124 (5) |
| $C_4$ Observability | 0.136 (4) | 0.201 (2) | 0.180 (2) | 0.160 (2) |
| $C_5$ Complexity | 0.099 (6) | 0.129 (3) | 0.131 (4) | 0.109 (6) |
| $C_6$ Compatibility | 0.174 (3) | 0.119 (5) | 0.148 (3) | 0.160 (2) |

Note: Rankings are shown in parentheses.

**Table 8**
Overall optimal local weights of the *cost-benefit* sub-criteria by stakeholder group.

| Criteria | Growers | Investors | Suppliers | Policy makers |
|---|---|---|---|---|
| $C_{11}$ Initial investment | 0.230 | 0.213 | 0.258 | 0.329 |
| $C_{12}$ Cost reduction | 0.396 | 0.267 | 0.482 | 0.218 |
| $C_{13}$ Revenue increase | 0.375 | 0.520 | 0.260 | 0.415 |

Nevertheless, some investors anticipate increased environmental regulations in the future. Two investors have begun accounting for greenhouse gas emission in their production processes, anticipating the potential extension of the cap-and-trade system, currently limited to the power generation sector, to the agricultural sector in China.

*Trialability* ranks as the second most important criterion among growers, while it is ranked fourth or fifth by other stakeholders. This can be attributed to the fact that *trialability* is directly related to the implementation of technology, which is particularly relevant for growers, the end-users of technologies. During interviews, several investors indicated that they would only adopt technologies that have demonstrated benefits. In China, the government often takes the lead in introducing new agricultural technologies, typically through demonstration programs. Once there are sufficient successful use cases for a technology, the investors typically do not conduct their own trials before adoption. One supplier confirmed that many large-scale greenhouses in China usually do not conduct trials.

*Observability* ranks second in importance for investors, suppliers, and policy makers, while it is of lesser importance (fourth) for growers. Growers indicated that their primary focus is yield and quality, while whether the technology has high observability is not a key concern for them. One investor notes that evaluating the benefits of a technology can be challenging if its effects are not easily observable, who for investors who lack specialized knowledge in agricultural production. A policy maker mentioned that *observability* is a primary factor to consider for the government when promoting innovative technologies.

*Complexity* is the least important criterion for growers, which contrasts with finding from many previous studies on agricultural technology adoption (e.g., Aubert et al., 2012; da Silveira et al., 2023; Gil et al., 2023; Reichardt et al., 2009). This discrepancy may stem from the unique profile of our grower sample, who are managers in high-tech greenhouses and most of whom hold a bachelor's degree or higher. Several growers stated that learning new technologies is an integral part of their job, and mastering complex technologies is a demonstration of their professional competence. *Complexity* is also a minor concern for policy makers. One policy maker mentions that modern farmers possess greater skills than farmers of the past, and the government aims to support skilled farmers who can serve as early adopters and knowledge disseminators within the farming network. *Complexity* is valued more highly among investors, ranking third in importance. One investor raised the concern that a complicated technology might incur indirect costs associated with employee training. Another investor expressed worries about the sunk cost of the initial investment if employees were unable to master the technology.

*Compatibility* is one of the primary concerns for growers, suppliers, and policy makers, but it ranks only fifth among investors. Investors tend to believe that incompatibility issues can be easily addressed. If the technology is incompatible with employees' working routines, standard operating procedures can be established to solve the issue. Similarly, modifying the physical infrastructure is not a problem, as such adjustments are typically one-time costs, provided that the economic benefits of the technology outweigh these costs. One supplier suggested that the importance of *compatibility* varies depending on the technology. For automation technologies, *compatibility* is less of a concern, whereas it is critical for sensors that handle data. One grower confirmed that growers prefer to work with an integrated data platform that has access to all sensor data. Additionally, a policy maker mentioned that when promoting greenhouse technologies, they consider not only those suited for high-tech greenhouses, but also those with potential for application in solar or plastic greenhouses, which together account for over 90 % of the protected horticultural area in China.

### 5.2. Performance scores of technologies on the given attribute

The performance scores of the technologies for each criterion, as elicited from the experts, along with their rankings, are shown in Table 9. The leaf temperature sensor has the lowest initial investment costs. A leaf temperature sensor generally costs <1000 euros. The investment costs for sap flow and leaf temperature sensors are comparable. In contrast, robotic technologies are significantly more expensive. Harvesting robots have the highest initial investment costs, followed by deleafing robots, and then scouting robotics. The estimated cost of a harvesting robot is between 80,000 and 150,000 euros, according to the experts. Additionally, experts predicted a significant reduction in the cost of robotics in the future. They also expect the business models of sensor and robotics producers will differ greatly, with robotics more likely to be adopted based on a leasing model. In this model, greenhouse firms do not need to purchase ownership of the robotics, but can lease them from agricultural equipment service providers.

Robotic technologies excel at reducing costs, as labor costs often represent a sizeable portion of operating costs. Automation technologies aim to replace human labor. Among robotic technologies, harvesting robots have the greatest potential for reducing operating costs, followed by deleafing robots and scouting robots. This is due to the higher labor demands associated with harvesting compared to deleafing and scouting. In contrast, sensors have limited capacity to reduce the operating costs of greenhouse production.

All five technologies have the potential to increase the revenue of greenhouse production. Among them, scouting robots offer the greatest potential for revenue increase by preventing production losses through early detection of pests and diseases. Then comes the sap flow sensor. Sap flow sensors can provide more detailed insights into crop development, which may lead to higher yields and improved crop quality, thus increasing revenue.

All experts rated the scouting robot as the most environmentally friendly technology because of its ability to detect and prevent pests and diseases, which reduces the need for chemical use. The deleafing robot could enhance environmental performance by performing more precise cutting than human labor, thereby reducing diseases incidence caused by inaccurate cutting and consequently reducing the use of chemicals. The leaf temperature sensor has the potential to reduce greenhouse gas emissions generated from energy use, provided that growers can improve temperature management based on sensor data.

Sensor technologies generally scored higher than robotics in terms of trialability. The installation of sap flow and leaf temperature sensors is relatively straightforward, as they can be clipped to the plant or positioned above the canopy. Once installed, they simply generate data without affecting greenhouse operations. In contrast, adopting robot technologies, especially deleafing and harvesting robots, requires growers to conduct multiple trials row by row to evaluate their performance. Among the robotic technologies, the scouting robot is the easiest to trial as it does not perform any actions on stems or fruits, making it less risky to trial. The harvesting robot received the lowest score for trialability. This is because if the harvesting robot fails to identify the correct cutting position, it risks damaging the main stem, resulting in a loss of production from the entire stem.

Robotic technologies generally scored higher than sensors in terms of observability. Among them, the harvesting robot scored the highest because its operation is relatively easy to understand, imagine, or visualize, even for those not familiar with greenhouse production. Whereas the deleafing and scouting robots are less intuitive, as the need for deleafing and scouting is not as well known. Sensor technologies scored the lowest on observability because they are much smaller and

**Table 9**
Performance scores and their rankings (in brackets) of technologies on the given criteria.

| Criteria | Sap flow sensor | Leaf temperature sensor | Deleafing robot | Harvesting robot | Scouting robot |
|---|---|---|---|---|---|
| $C_{11}$ Initial investment | 0.370 (2) | 0.389 (1) | 0.083 (4) | 0.067 (5) | 0.091 (3) |
| $C_{12}$ Cost reduction | 0.082 (4) | 0.080 (5) | 0.274 (2) | 0.389 (1) | 0.176 (3) |
| $C_{13}$ Revenue increase | 0.207 (2) | 0.195 (3) | 0.160 (5) | 0.169 (4) | 0.269 (1) |
| $C_2$ Environment | 0.166 (3) | 0.198 (2) | 0.125 (4) | 0.108 (5) | 0.403 (1) |
| $C_3$ Trialability | 0.339 (2) | 0.371 (1) | 0.087 (4) | 0.071 (5) | 0.131 (3) |
| $C_4$ Observability | 0.071 (5) | 0.094 (4) | 0.244 (2) | 0.360 (1) | 0.231 (3) |
| $C_5$ Complexity | 0.090 (5) | 0.111 (4) | 0.310 (1) | 0.277 (2) | 0.213 (3) |
| $C_6$ Compatibility | 0.313 (2) | 0.361 (1) | 0.102 (2) | 0.073 (5) | 0.151 (3) |

Note: Rankings are shown in parentheses.

therefore less visible compared to robotic technologies.

Sensors generally scored lower on complexity than robotic technologies. According to the taxonomy of precision agriculture studies (Miller et al., 2019), robotic technologies fall into the category of embodied knowledge technologies, while sensors are classified as information-intensive technologies. For robotics, the value of the technology is 'embodied' within the system itself, meaning that end-users do not require specialized skills to use it effectively. However, with sensors, although they are easy to install, experts tend to believe that it is challenging for growers to translate the data generated by sensors, especially sap flow sensors, into meaningful managerial decisions. Growers need to have good understanding of plant physiology to fully leverage the data generated by sap flow and leaf temperature sensors.

In terms of compatibility, robotic technologies are less compatible than sensor technologies because they require more modifications to the physical infrastructure of the greenhouse, such as the pipe-rail system or the power station. In contrast, sensors can be easily installed with little or no change to the existing greenhouse infrastructure. The harvesting robot received the lowest score for compatibility. Successful integration of the harvesting robot requires significant modifications to the logistics system to enable automatic grading and packing of fruit immediately after harvesting. The scouting robot needs a computer connection to track its movements and record data on pests and diseases.

### 5.3. Overall performance scores and credal rankings of technologies

By combining stakeholder preferences and expert scores, we obtained the average overall performance scores and rankings of the technologies for each stakeholder group, as shown in Table 10. Between the two sensor technologies, the leaf temperature sensor scored higher than the sap flow sensor across all stakeholder groups. Of the five technologies, the deleafing robot received the lowest overall performance score across all stakeholder groups. The harvesting robot achieved the highest score based on the preferences of suppliers, while the scouting robot received the highest score according to the preferences of investors.

The credal rankings and overall performance scores of the technologies for each stakeholder group are visualized in Figs. 4 to 7. The relationship between technology performances is indicated by the arrow direction and weight. Rankings were determined by applying a threshold of 0.5 to the credal rankings of the technologies.

From the grower's perspective, the leaf temperature sensor ranks highest. Although the sap flow sensor is ranked second, a confidence of

**Table 10**
Overall performance scores and rankings (in brackets) of technologies by stakeholder group.

| Technology | Grower | Investor | Supplier | Policy maker |
|---|---|---|---|---|
| Sap flow sensor | 0.210 (2) | 0.190 (4) | 0.187 (4) | 0.208 (3) |
| Leaf temperature sensor | 0.233 (1) | 0.210 (2) | 0.209 (3) | 0.231 (1) |
| Deleafing robot | 0.168 (5) | 0.181 (5) | 0.185 (5) | 0.166 (5) |
| Harvesting robot | 0.184 (4) | 0.202 (3) | 0.211 (1) | 0.180 (4) |
| Scouting robot | 0.204 (3) | 0.218 (1) | 0.208 (3) | 0.216 (2) |

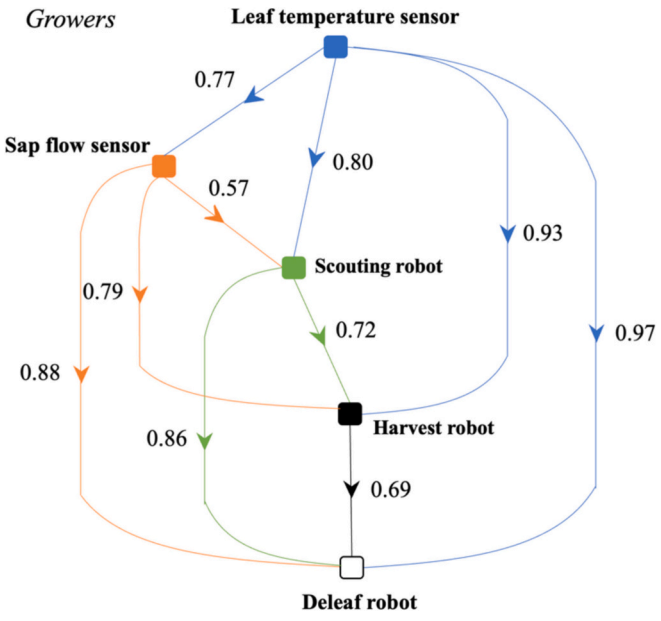



**Fig. 4.** Credal ranking on the overall performance of technologies – growers' perspective.

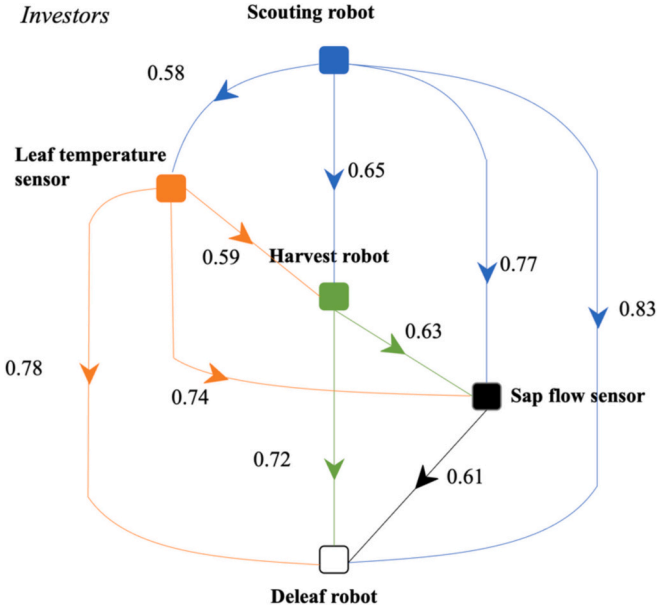



**Fig. 5.** Credal ranking on the overall performance of technologies – investors' perspective.

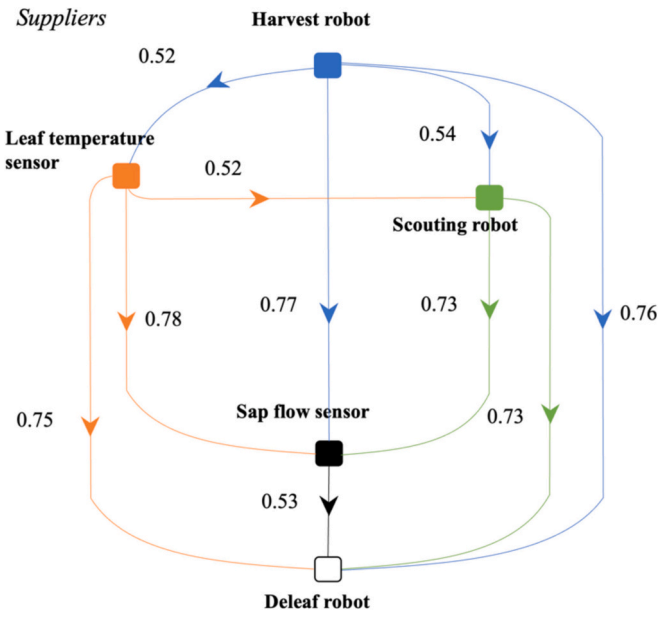



**Fig. 6.** Credal ranking on the overall performance of technologies – suppliers' perspective.

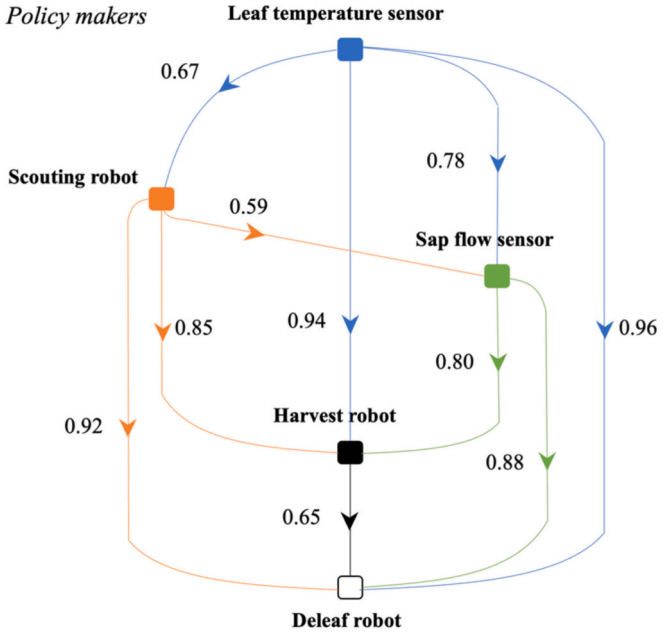



**Fig. 7.** Credal ranking on the overall performance of technologies – policy makers' perspective.

0.57 between it and the scouting robot implies that some suppliers considered the scouting robot to be more interesting. The harvesting robot is ranked fourth by growers, and the deleafing robot is ranked last.

For investors, the scouting robot receives the highest overall performance score, followed by the leaf temperature sensor and the harvesting robot. However, we cannot definitively conclude that the scouting robot ranks higher than the other two technologies, as the confidence of the credal rankings between the scouting robot and the leaf temperature sensor is only 0.58. The sap flow sensor is less attractive to investors and is ranked fourth. The delafing robot ranks last in terms of investor preferences.

For suppliers, the harvesting robot, leaf temperature sensor, and scouting robot are the top-ranked technologies, with the overall performance scores closely aligned. This is reflected in the confidence levels between each pair of the three technologies, which are just above the 0.5 threshold. Sap flow sensor and deleafing robot are the lowest ranked technologies and their overall performance scores are also similar.

The leaf temperature sensor receives the highest score calculated using the weights of policy makers, followed by the scouting robot and the sap flow sensor. The harvesting robot, which is ranked first by suppliers, is only ranked fourth by policy makers. The deleafing robot is ranked last across all stakeholder groups.

## 6. Conclusions and discussion

The adoption of emerging sensor and automation technologies is essential for advancing the digitalization of greenhouse production. However, it remains uncertain which technologies are most likely to achieve widespread acceptance during the diffusion process. This study aimed to dentify technologies with the highest diffusion potential by examining the preferences of various stakeholders in Chinese greenhouse sector, combined with an assessment of technology performance across different dimensions defined by the DOI theory. Stakeholder weights for the technology attributes and the relative importance of each technology were elicited using the Bayesian BWM. An additive value function was then employed to generate the overall performance scores for these technologies.

### 6.1. Main findings

Stakeholders show heterogeneous preferences for the technology attributes. For all stakeholder groups, the cost-benefit of technology was the most important attribute. The observability of technology is highly valued by investors, technology suppliers, and policy makers. Meanwhile, growers place a higher emphasis on the technology's trialability and compatibility. Interestingly, growers ranked complexity of technology as the least important attribute, a finding that differs from previous research (Aubert et al., 2012; Reichardt et al., 2009; Wang et al. (2024)). Policy makers are more concerned about the environmental impact of technology, ranked it fourth. In contrast, it was the least important among investors and technology suppliers.

Robotic technologies generally require a higher initial investment compared to sensor technologies, but they offer greater potential for cost reduction. Among the five technologies, the scouting robot performs the best in terms of increasing revenue and reducing environmental impacts. Compared to sensors, robotic technologies tend to have lower trialability and compatibility, although they score higher on observability. In contrast, sensor technologies have higher complexity, as they typically require specific expertise to translate sensor data into meaningful managerial decisions.

These technologies also present varying diffusion potentials across different stakeholder groups. The leaf temperature sensor has the highest overall performance score among growers and policy makers. The scouting robot and the harvesting robot received the highest overall performance scores among investors. The deleafing robot received the lowest overall performance score across all stakeholder groups.

### 6.2. Contributions and practical implications

This study presents the first comprehensive multi-criteria assessment of sensor and robotic technologies from a multi-stakeholder perspective. While our approach is applied to greenhouse technologies, it can also be adapted to other technologies or MCDM problems. This is also the first study to combine the diffusion of innovation theory with the Bayesian BWM, distinguish it from other technology assessment studies that often adopt a narrow techno-centric view. By emphasizing factors crucial to successful technology diffusion, this study bridges the gap between technology assessment and innovation adoption studies. The inclusion

of both experts and stakeholders in the evaluation process ensured a broader range of perspectives, resulting in more robust results than evaluations conducted solely by experts (Grunwald, 2009).

Moreover, this study contributes to the technology assessment literature by introducing a probabilistic evaluation score through the application of Bayesian BWM. By combining stakeholder preferences and expert scores, both modeled as Dirichlet distributions, we approximated the probability distributions of the overall performance scores of technologies. This approach allows for a more nuanced probabilistic ranking of technologies, rather than relying solely on the absolute scores. This approach is particularly well-suited to early-stage assessments of technologies where limited information is available.

A practical implication of this study for stakeholders in the greenhouse farming sector in China is that they now have a better understanding of the priorities of other stakeholders. Since some attributes can be directly influenced by policy makers or technology suppliers. Stakeholders can use the findings of this study to their advantage by influencing these determinants, thereby increasing the likelihood of success for the technologies that they are in favour of. The heterogeneous preferences among stakeholders underscore the need for tailored strategies in promoting innovative technologies. For example, to convince growers, policy makers and technology suppliers should focus on showcasing the compatibility and trialability of through demonstration programs. Additionally, the performance scores offer valuable insights into the strengths and weaknesses of each technology, guiding stakeholders in making informed decisions.

### 6.3. Limitations and future research

While this study provides valuable insights, it is important to acknowledge its limitations. First of all, the results of the evaluation are highly dependent on the criteria included in the evaluation framework. In this study, the evaluation criteria are based on the DOI theory. Although it is widely used in agricultural innovation studies, the DOI theory may not fully capture the complexities of agricultural technologies. Lyytinen and Damsgaard (2001) criticized the completeness of the technology attribute list defined by the DOI, questioning whether all innovations can be adequately characterized using these attributes. Future work could consider additional criteria, such as data safety (Shang et al., 2021), user safety (Hemming, 2020), reliability (van de Kaa et al., 2020) and social impact (Schimmelpfennig, 2016), which have been used in other studies to enrich the evaluation framework.

Another limitation of this study is its "static" nature; the assessment does not account for technological progress that may occur in the future. The evaluation was based on the current costs and capabilities of sensor and robotic technologies, which are continuously advancing. For example, experts predict significant improvements in the speed and cost reduction of harvesting robots in the future. An interesting avenue for future research is to investigate whether the performance of these technologies changes over time. Conducting a longitudinal study that tracks the rate of adoption of these technologies over time and validates the findings of this study is another promising direction for future research.

Additionally, the study evaluates technologies independently, without considering potential interdependencies between them. For example, an expert indicated that effective leave pruning is essential for the successful operation of harvesting robots. Future research could explore the assessment of technology bundles to capture these interdependencies.

One challenge of technology assessment is the multi-dimensional integration of various evaluation criteria (Grunwald, 2009). One potential limitation of our approach is the use of the additive value function, which calculates the overall performance score as the sum of stakeholder weights multiplied by expert scores. This aggregation assumes that the criteria are mutually preferentially independent, which may not always be the case. To better account for interactions between criteria, future research could apply the nonadditve BWM method proposed by Liang et al. (2023).

Additionally, this assessment converts technology performance on disparate criteria, which may be partially incommensurable, to a common scale. The calculations are highly dependent on the specific weighting and aggregation procedure used, and the resulting weights are subjective to the assumptions and subjective scaling procedures of the Bayesian BWM, which also determines how the quantitative results should be interpreted appropriately. The results of the assessment should not be seen as a replacement for decision-making, but rather as information to support the decision-making process.

## CRediT authorship contribution statement

**Xinyuan Min:** Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Jaap Sok:** Conceptualization, Methodology, Supervision, Writing – review & editing. **Tian Qian:** Data curation, Funding acquisition. **Weihao Zhou:** Data curation. **Alfons Oude Lansink:** Funding acquisition, Methodology, Supervision, Writing – review & editing.

## Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used GPT-4 in order to improve language and readability. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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## Declaration of competing interest

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

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## Data availability

Survey data can be accessed via
Evaluating sensor and robotic technologies in the Chinese greenhouse sector using the Bayesian best-worst method: a multi-stakeholder perspective (Original data) (Mendeley Data)

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