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Unraveling users' digital technology adoption in horticulture 4.0: A systematic review and meta-analysis

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A R T I C L E I N F O

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A B S T R A C T

Horticultural production is often capital intensive and generates high economic value, creating strong potential for the use of digital technologies (DTs). However, their adoption remains constrained by a wide range of determinants. Existing studies have examined DT adoption in horticulture from different perspectives and theoretical frameworks, but the evidence remains fragmented. This systematic review synthesizes current knowledge on DT adoption by distinguishing three adoption constructs: willingness to adopt (WTA), behavioral intention (BI), and usage behavior (UB). Following PRISMA guidelines, 129 empirical studies were included in the systematic review, of which 54 contributed data to the meta-analysis. The qualitative synthesis shows that studies of BI mainly focus on psychological and social determinants, whereas studies of UB more often examine technical, knowledge, social, infrastructure, and institutional determinants. Evidence on WTA remains comparatively limited. The meta-analysis shows that age, social influence, perceived usefulness, and perceived ease of use are significantly associated with BI. For UB, significant positive associations were found for sex, education level, training participation, planting area, farming income, household income, organization or cooperative membership, risk attitude, social network, and social influence. Subgroup analyses further showed that some associations with UB varied across geographic regions, crop systems, and DT types. The findings show that the relevance of adoption determinants differs across WTA, BI, and UB and varies across horticultural contexts. This study provides a more differentiated understanding of DT adoption in horticulture and offers evidence for developing more targeted policy, technical, and institutional support.

1. Introduction

Digital technologies (DTs) are increasingly transforming horticultural production by enabling data-driven decision making, automation, and improved resource management. Applications such as sensors, Internet of Things (IoT) platforms, robotics, artificial intelligence (AI), digital twins, and decision support systems are being implemented to improve productivity, labor efficiency, product quality, and environmental sustainability [1–3]. As labor shortages, climate variability, rising production costs, and stricter sustainability requirements intensify [4–7], these technologies are widely regarded as key enablers of the transition towards Horticulture 4.0 (see Appendix A for an overview).

Despite their technological potential, the adoption of DTs in horticulture remains uneven. Studies have shown that growers may recognize the potential benefits of DTs but still postpone or discontinue implementation because of high investment costs, technical uncertainty, limited interoperability, insufficient digital skills, or inadequate institutional support [8–11]. This suggests that successful digital transformation depends not only on the availability of technologies but also on individual perceptions, farm and organizational capabilities, and the broader institutional environment.

Understanding technology adoption is particularly important in

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horticulture because horticultural production differs fundamentally from agriculture as a whole. Compared with large scale arable farming, horticulture is characterized by high-value and often highly perishable crops, intensive management, considerable labor requirements, biological variability, and substantial investments in production systems such as protected cultivation and precision technologies [12,13]. These characteristics may increase both the potential benefits and the risks associated with adopting DTs. Findings from broader agricultural adoption studies may therefore not fully capture the specific conditions of horticultural production systems [14,15]. Previous reviews have summarized DTs in agriculture or described their applications within horticulture, but several important gaps remain.

First, previous reviews often aggregate evidence across agricultural sectors, which may obscure adoption patterns that are specific to horticultural production systems. Findings from broader agricultural contexts may not adequately explain adoption dynamics in horticulture. Second, technology adoption is commonly conceptualized as a binary outcome (adoption versus non-adoption) or examined primarily through behavioral intention [16]. However, the decision to adopt a technology develops over time [17]. Farmers may first evaluate whether technology is acceptable or desirable, subsequently form an intention to adopt, and only later translate this intention into actual usage. Distinguishing between willingness to adopt (WTA), behavioural intention (BI), and usage behaviour (UB) is therefore important for examining whether different determinants are associated with different adoption constructs and for understanding why positive intentions do not always correspond with actual technology use. Third, existing studies apply diverse theoretical frameworks, including the technology acceptance model (TAM), theory of planned behavior (TPB), unified theory of acceptance and use of technology (UTAUT), diffusion of innovations (DOI), and technology–organization–environment (TOE). While these theories provide valuable insights into determinants at different stages of adoption, each framework captures only part of the adoption process. This limits a comprehensive understanding of how the relevance of different determinants varies from willingness and intention to actual technology use [18].

To address these gaps, this study conducts a systematic review and meta-analysis of empirical studies on DT adoption in horticulture. Rather than treating adoption as a single outcome or assuming a universal sequence, we distinguish WTA, BI, and UB as three analytical constructs. We examine the determinants associated with WTA, BI, and UB, the theoretical perspectives used in this literature, and how these patterns vary across horticultural contexts. Specifically, this study addresses the following research questions:

(1) How has digital technology adoption in horticulture been studied in terms of geographical focus, theoretical foundations, and methodological approaches?
(2) What determinants have been identified as associated with digital technology adoption in horticulture?
(3) To what extent do adoption determinants differ between willingness to adopt, behavioral intention, and usage behavior?

To answer these questions, we conducted a systematic review of 129 empirical studies following the PRISMA guidelines. Of these studies, 54 provided sufficient quantitative evidence for meta-analysis. The novelty of this study lies in distinguishing WTA, BI, and UB as analytically distinct adoption constructs to better understand how the relevance of adoption determinants differs across these constructs. These findings also provide practical implications for technology developers, policymakers, and growers seeking to support digital transformation.

2. Scope of review

Digital technologies (DTs) are used in this review as a broad umbrella term covering a wide range of information, communication, sensing, automation, and decision support technologies applied in horticultural production, management, and related supply chain activities [19]. Examples include information and communication technology (ICT), the Internet of Things (IoT), artificial intelligence (AI), remote sensing, robotics, farm management information systems, blockchain, and e-commerce platforms. These technologies differ in their functions, costs, and implementation requirements, and their adoption may therefore involve different determinants. A broad definition was adopted to capture this technological diversity rather than fragment the evidence by individual technology.

The review is restricted to horticulture because its production characteristics differ from those of agriculture more broadly. Horticultural systems often involve high value crops, intensive management, perishability, substantial labor requirements, and considerable investment in protected cultivation and precision technologies. These characteristics may shape technology adoption differently from broad acre agricultural systems and therefore justify examining horticulture as a distinct review context. The review covers vegetables, fruits, flowers, and ornamental crops across different production systems. Clear operational criteria were applied to distinguish horticultural crops from arable crops, with the detailed classification and eligibility criteria provided in Appendix B.

Technology adoption can be conceptualized and measured in different ways. Established technology adoption theories distinguish behavioral intention from actual technology use, treating them as conceptually different constructs [20,21]. However, in some studies, WTA and BI are not clearly distinguished and are operationalized in similar ways. To organize this heterogeneous evidence, this review treats WTA, BI, and UB as separate analytical constructs. WTA refers to willingness to adopt a DT, BI refers to the intention to adopt a DT, and UB refers to its reported implementation or use. This distinction allows the determinants associated with willingness, intention, and actual use to be compared more clearly.

3. Methods

3.1. Study design

This study combines a systematic literature review with a quantitative meta-analysis to synthesize empirical evidence on determinants associated with digital technology (DT) adoption in horticulture. The review was conducted and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [22]. Studies were grouped according to the adoption constructs they examined: willingness to adopt (WTA), behavioural intention (BI), and usage behaviour (UB). The systematic review synthesized the characteristics of the included studies, the frequency of reported determinants, and the direction of their associations across WTA, BI and UB. All studies meeting the eligibility criteria were included in the systematic review, while only those providing sufficient statistical information for effect size calculation were included in the meta-analysis.

3.2. Literature search

3.2.1. Databases

A comprehensive literature search was conducted to identify empirical studies examining determinants associated with DT adoption in horticulture. A systematic literature search was conducted on the Web of Science, Scopus, Science Direct, and PubMed. Google Scholar was used as a supplementary search source. These databases were selected because together they provide broad coverage of agricultural sciences, horticulture, information systems, environmental sciences, and interdisciplinary technology adoption research. For each search in Google Scholar, the first 200 records ranked by relevance were screened, in line with the recommendation of Bramer et al. (2017) [23]. Backward and forward citation searching was conducted for all included studies.

Backward citation searching involved screening the reference lists of the included studies, while forward citation searching involved screening studies that cited the included articles. Records were imported into the Zotero 6.0 Reference Manager software, and duplicates were removed [24].

3.2.2. Search period

The literature search covered studies published from 2001 to 2026. The initial database search was conducted in March 2025, followed by an updated search in July 2026, prior to manuscript revision to capture recently published studies in this rapidly evolving research field. Only studies published in English were considered because of resource constraints.

3.2.3. Search strategy

Because terminology related to horticulture and DTs varies across disciplines, a concept based search strategy was developed. The search terms were organized into four conceptual groups: (1) horticulture, (2) adoption, (3) determinants, and (4) digital technologies. Within each concept, synonyms and related terms were connected using the Boolean operator OR, whereas the four concepts were combined using AND. Truncation (*) and phrase searching were applied where permitted by individual databases to capture singular and plural word forms and spelling variations. Given the large number of terms used to describe DTs, a single comprehensive Boolean string could become overly broad and ambiguous. We therefore conducted a series of structured searches for specific technologies. Table 1 presents representative search terms, and the exact search strings used for each database are provided in Appendix C in a reproducible format.

To improve search sensitivity, the search was conducted in two sequential rounds. The first round used broad terms related to digitalization, such as digital agriculture, precision agriculture, smart farming, and agriculture 4.0, to identify the general literature on DT adoption in horticulture. Technologies identified during the first round were then used to develop the second round of searches. This second round covered 23 individual DTs reported in horticultural production and supply chains. This approach reduced the likelihood of missing studies that referred only to specific technologies rather than broader digitalization terms.

3.3. Eligibility criteria and study selection

The eligibility criteria were established before the literature search to ensure consistent study selection and to define the scope of the review. Studies were included when they examined empirical determinants of DT adoption within horticultural production systems. Eligibility was assessed independently by two reviewers through title and abstract screening, followed by full-text assessment where necessary. Disagreements were resolved through discussion until consensus was reached.

Table 1
Selected keywords.

Search concept	Search terms
Horticulture	horticultur*, greenhouse*, vegetable*, fruit*, floricultur*, ornamental*, nursery*, orchard*
Adoption	adopt*, accept*, intention*, willingness*
Determinants	factor*, determinant*, driver*, barrier*, facilitator*
Digital technologies	precision agriculture, smart farming, digital agriculture, agriculture 4.0, information and communications technology, ICT, Internet of Things, IoT, blockchain, artificial intelligence, AI, deep learning, machine learning, cloud computing, big data, e-commerce, e-business, digital twins, remote sensing, farm management information system, decision support system, unmanned aerial vehicles, UAV, drone, wireless sensor network, smartphone, mobile app, variable rate technology, variable rate application, information technology, information system

3.3.1. Inclusion criteria

Studies were included when they satisfied all of the following criteria:

1. The study examined at least one horticultural crop or horticultural production system;
2. The study examined one or more DTs used in production, management, marketing, or supply chain activities relevant to horticulture;
3. The study empirically analyzed determinants associated WTA, BI, or UB;
4. The study reported original empirical data using quantitative, qualitative, or mixed methods research designs;
5. The publication was written in English and published in a journal, conference proceedings or book chapters.

To ensure consistent study selection, horticulture was defined according to structural characteristics rather than individual crop names. The distinction between horticultural and arable cropping systems was based on production environment, management intensity, labor requirements, crop characteristics, perishability, and production objectives.

3.3.2. Exclusion criteria

Studies were excluded when they:

6. Focused exclusively on arable crops, livestock, forestry, fisheries, or aquaculture and did not include a horticultural context;
7. Examined DTs without analyzing determinants associated with adoption;
8. Described technical performance, engineering development, or algorithm design without studying adoption;
9. Consisted of editorials, doctoral theses, master's dissertations, errata, encyclopedia entries, reports, review articles, conceptual papers, opinion papers, or conference abstracts;
10. Did not provide sufficient information to classify the investigated adoption constructs (WTA, BI, or UB).

Where multiple publications reported results from the same dataset, only the most complete or most recent publication was retained.

3.3.3. Screening and study selection

Following the removal of duplicate records, titles and abstracts were screened against the eligibility criteria. Potentially relevant articles then underwent full text assessment. Reasons for exclusion at the full text stage were documented and summarized in the PRISMA flow diagram (Fig. 1). Records identified through Google Scholar and backward and forward citation searching were assessed using the same eligibility criteria and screening procedure.

A total of 3049 records were initially identified through four database searches. After removing duplicates, 1211 records remained for title and abstract screening. Following title, abstract, and full-text assessment, 57 empirical studies met the eligibility criteria and were included in the systematic review. In addition, 341 records were identified through supplementary searches on Google Scholar, backward and forward citation searching of the included studies. After removing 130 records that overlapped with those identified through other databases, 211 studies were sought for retrieval, of which 72 met the eligibility criteria for inclusion. As a result, a total of 129 studies were ultimately included in this systematic review, comprising 116 journal articles, 12 conference papers, and 1 book chapter.

Of these 129 studies, 27 reported qualitative or descriptive data only, 26 presented results for mixed agricultural systems from which outcomes specific to horticulture could not be isolated, and 22 did not provide sufficient statistical information to calculate effect sizes. Consequently, 54 studies were included in quantitative meta-analysis.

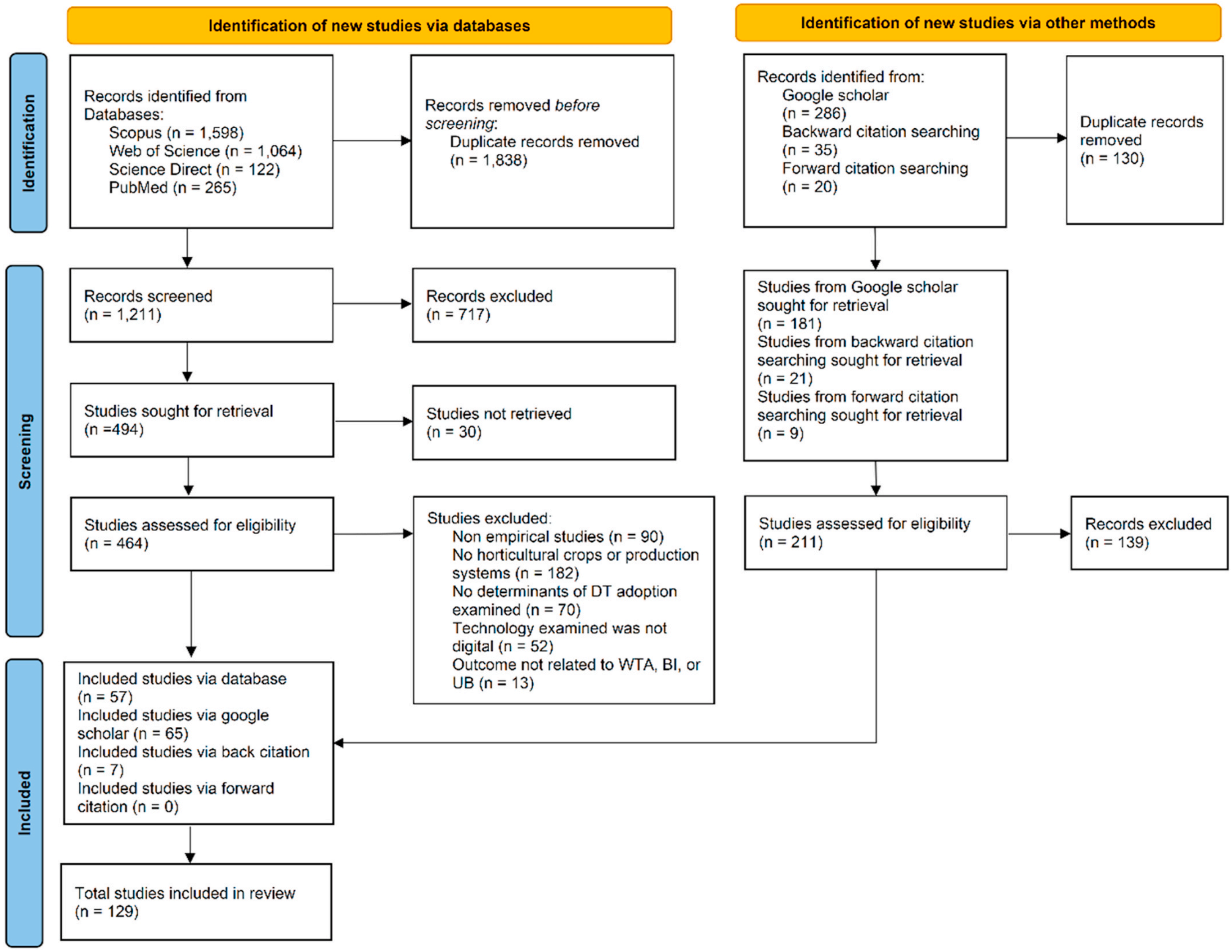

Fig. 1. PRISMA flow chart for this systematic review [22].

3.4. Data extraction

Two reviewers independently extracted the study characteristics using a standardized extraction form developed prior to the review. A standardized extraction protocol was piloted on a small subset of studies prior to full extraction. For each study, study characteristics, adoption constructs, and determinants examined were extracted. For studies eligible for quantitative synthesis, the information required for effect size calculation was also extracted (sample size, effect estimates, standard errors, test statistics, confidence intervals or sufficient information for effect size conversion). Disagreements between the two reviewers were resolved through discussion until consensus was reached.

3.5. Methodological quality assessment

The methodological quality of the included studies was assessed using the Mixed Methods Appraisal Tool (MMAT), version 2018 [25]. MMAT was selected because the included evidence comprised qualitative, quantitative, and mixed methods studies, allowing different empirical research designs to be assessed within a common appraisal framework [26]. The appraisal procedure followed the MMAT 2018 user guide.

Each study first underwent two screening questions to confirm empirical eligibility. Studies were subsequently evaluated using the five methodological criteria corresponding to their respective study design (qualitative, quantitative descriptive, quantitative non-randomized, quantitative randomized or mixed methods). Each criterion was rated as Yes, No, or Can't tell. For descriptive comparison and sensitivity analysis, an additional summary percentage was calculated following Lei et al. (2026) [27] and Parikh et al. (2022) [28]. The number of criteria rated Yes was divided by five and expressed as a percentage. Studies were classified as high quality (≥80%), moderate quality (60%), or low quality (<60%). Two reviewers independently performed the quality assessment, with disagreements resolved through discussion until consensus was reached. The complete quality assessment for all included studies is provided in Appendix D.

Methodological quality was not used as an exclusion criterion for either the systematic review or the primary meta-analysis, as this review aimed to provide a comprehensive synthesis of the available evidence. Instead, methodological quality was considered when interpreting the findings, and sensitivity analyses were conducted by repeating the meta-analyses after excluding studies classified as low methodological quality.

3.6. Effect size calculation

Only determinants examined in at least five independent studies were eligible for meta-analysis [29]. Because the included studies reported associations using a variety of statistical measures, a common effect size metric was required. Pearson's correlation coefficient (r) was selected because it provides a standardized measure of association and can be derived from the diverse statistical outputs commonly reported in observational technology adoption studies [30,31].

Where studies directly reported Pearson's r, these values were extracted. Otherwise, reported statistics, including t-values, χ^2 statistics, standardized regression coefficients (β), multiple regression coefficients, structural equation modelling coefficients, and logistic and probit regression coefficients, were converted to Pearson's r using established statistical conversion procedures [32–36]. The complete set of conversion equations is provided in Appendix E. To maintain statistical independence, only one independent study level effect size for each determinant was included in each meta-analysis. When multiple statistical models reported estimates for the same determinant, adjusted estimates were preferred over unadjusted estimates, and the estimate from the fully adjusted or primary model was selected. When multiple eligible effect sizes for the same determinant were reported from the same sample across different DT types, these estimates were treated as dependent outcomes and combined into a single study level effect size [37]. For ordered categorical determinants represented by multiple contrasts, the contrast between the highest category and the lowest/reference category was selected. Effect directions were harmonized so that positive values consistently indicated a positive association with WTA, BI, and UB. Where necessary, signs were reversed according to the original variable coding or reference category.

Prior to pooling, correlation coefficients were transformed to Fisher's z to stabilize sampling variance and improve statistical normality, and subsequently back transformed to Pearson's r for interpretation of the pooled effect sizes [38]. Effect sizes were interpreted according to Cohen's conventional thresholds, with correlations of 0.10–0.29 regarded as small, 0.30–0.49 as moderate, and ≥0.50 as large [39].

3.7. Data synthesis

Random-effects meta-analysis was performed to account for the expected heterogeneity among studies arising from differences in geographical regions, research populations, crop systems, and DT types. Statistical heterogeneity was assessed using Cochran's Q statistic [40] and the I^2 statistic [41], with statistical significance evaluated at $p < 0.05$. The unit of analysis was the individual study.

3.8. Subgroup analysis and robustness checks

Subgroup analyses were conducted only for determinants represented by at least ten independent studies and exhibiting substantial heterogeneity ($I^2 \geq 75\%$). Studies were stratified by geographical region, publication year, study population, DT type, and crop system to explore potential sources of heterogeneity. Differences between subgroups were assessed using the Q test for between group heterogeneity, with $p < 0.05$ indicating a statistically significant subgroup difference.

Sensitivity analyses were conducted to assess the robustness of the pooled estimates to methodological quality. Each meta-analysis was repeated after excluding studies classified as low methodological quality based on the summary percentage described in Section 3.5. The direction, magnitude, and statistical significance of the pooled effect sizes were then compared with those of the primary analyses.

Publication bias was assessed using funnel plots and Egger's regression test [42,43]. Where publication bias was indicated, the trim-and-fill procedure was applied to evaluate the robustness of the pooled effect sizes. All quantitative analyses were performed using Comprehensive Meta-Analysis (CMA), version 4.0.

4. Results

4.1. Study characteristics

A total of 129 studies met the final inclusion criteria for the systematic review on determinants associated with the adoption of digital technologies (DTs) in horticulture. The included studies were analyzed according to several research characteristics, including publication year, geographical region, adoption constructs investigated, DT types, crop systems, study populations, study designs, sampling strategies, analytical methods, theoretical frameworks, and academic landscape. Fig. 2 provides an overview of the main characteristics of the included studies.

4.1.1. Publication trends and geographical distribution

The literature on determinants associated with DT adoption in horticulture dates back to 2003, with a marked increase in the number of publications since 2020 and a particularly high proportion of studies published in 2022. The distribution of included articles over time is presented in Appendix F. The included studies covered 40 individual countries, while eight studies examined multiple countries or regions (see Fig. 3). Asia accounted for the largest share of studies (50.39%), followed by Europe (20.16%), Africa (7.75%), South America (6.98%), North America (5.43%), and Oceania (3.10%). China was the most frequently represented individual country, with 17 studies (13.18%), followed by India, with 12 studies (9.30%).

4.1.2. Adoption constructs investigated

The included studies examined three principal adoption constructs: willingness to adopt (WTA), behavioral intention (BI), and user behavior (UB). Among the included studies, 79 focused on determinants of UB, 28 examined BI, and 10 investigated WTA. In addition, six articles examined determinants of both BI and UB, while another six investigated determinants of both WTA and UB (Fig. 2).

4.1.3. Digital technology types

To account for functional differences between DTs, studies were classified into two categories. Digital technologies for production (DTP) comprised technologies that directly support or automate production processes, including sensors, Internet of Things (IoT) applications, variable-rate technologies, robotics, and precision agriculture applications. Digital technologies for communication (DTC) comprised technologies that primarily facilitate information exchange, decision support, coordination, and marketing, including farm information management systems, mobile applications, advisory platforms, and e-commerce systems. 40.31% of the studies investigated DTC, while 38.76% investigated DTP; the remaining studies examined both DTC and DTP.

4.1.4. Study population and crop systems

The included studies primarily focused on horticultural farmers or growers (77.52%), including individual farmers and managers of horticultural enterprises. Multiple stakeholder groups, including food processors, experts, and government organizations, were examined in 19.38% of the studies, whereas experts alone (1.55%), wholesalers (0.78%), and technology providers (0.78%) were rarely investigated.

The reviewed literature covered diverse horticultural production systems, although their distribution was uneven. Open-field horticulture accounted for the largest proportion of studies ($n = 58$), followed by mixed production systems ($n = 11$). By contrast, soil-based greenhouse systems ($n = 2$), soilless greenhouse systems ($n = 1$), and vertical farming ($n = 1$) were rarely represented, while 56 studies did not specify a particular production system. The types and applications of DTs investigated also varied across production systems (see Fig. 4). Studies of open-field horticulture most frequently examine robots, sensors, smartphones, blockchain, variable-rate technologies (VRT), and decision-support systems for applications such as pest management, harvesting, environmental monitoring, and irrigation management. Greenhouse studies primarily focused on Internet of Things (IoT) applications, enterprise resource planning (ERP) systems, and resource-management technologies for irrigation, fertilization, and farm

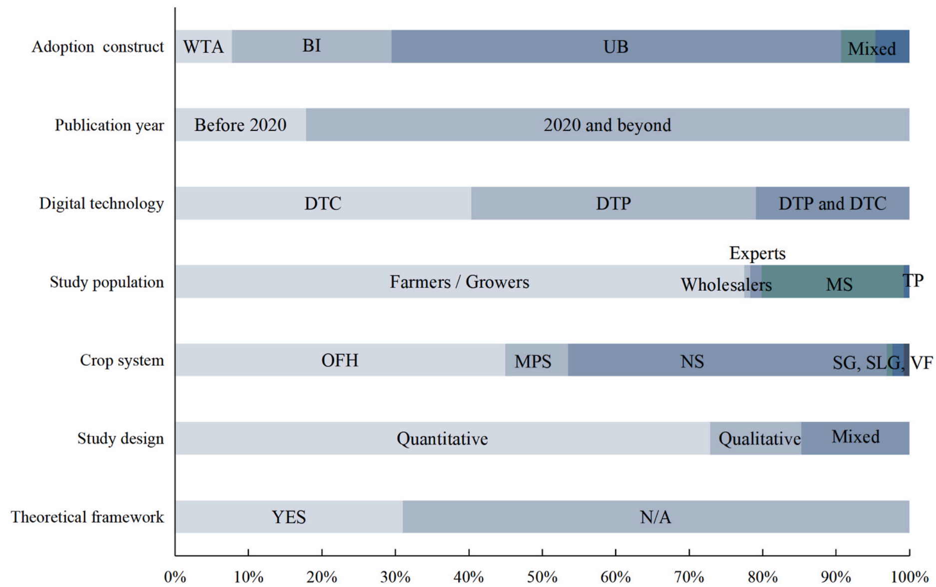

Fig. 2. Research characteristics of 129 included articles in systematic review.
Legend: WTA = willingness to adopt; BI = behavioral intention; UB = usage behavior; OFH = open field horticulture; SG = soil-based greenhouse; SLG = soilless greenhouse; VF = vertical farming; MPS=Mixed production systems ; NS=Not specific ; DTC = digital technology of communication; DTP = digital technology of production; MS = multiple stakeholders (growers, contractors, commission agents, wholesalers, food processors, exporters, experts, agricultural technology firms, government organization, R&D organizations, and GNO); TP = technology providers; YES = the article applied at least one theoretical model; N/A = no theoretical model was applied.

management. The single study on vertical farming focused mainly on digital monitoring and remote-control systems.

4.1.5. Study designs, sampling strategies and analytical methods

Of the 129 included articlesstudies, 72.87% employed quantitative methods, 12.40% used qualitative methods, and 14.73% adopted mixed methods designs. A wide range of sampling strategies was reported. Purposive sampling was the most frequently used approach (16.28%), followed by simple random sampling (10.85%) and stratified random sampling (8.53%). Other reported strategies included census sampling, cluster sampling, convenience sampling, two-stage random sampling, multistage random sampling, non-probability sampling, and snowball sampling.

A similar wide range of analytical methods was employed. Structural equation modeling (SEM), including partial least squares SEM (PLS-SEM), generalized SEM (GSEM), and covariance-based SEM (CB-SEM), was the most frequently used analytical method (19.38%), followed by binary logistic regression (7.75%), multiple linear regression (6.20%), and descriptive statistics (5.43%). Other analytical methods included ordinary least squares (OLS) regression, probit models, heckman selection models, negative binomial regression, poisson regression, and chi-square (χ^2) tests.

4.1.6. Theoretical frameworks

Of the 129 included studies, 31.01% explicitly applied at least one theoretical framework to explain determinants of DT adoption. Studies drawing on multiple theoretical frameworks were counted under each relevant framework. TAM was the most frequently applied framework, appearing in 17studies, followed by DOI (n = 11), TOE (n = 8), TPB (n = 5), and UTAUT (n = 5). Less frequently used frameworks included TAM3, UTAUT2, behavioral reasoning theory (BRT), resource-based view (RBV), theory of herd behavior (THB), perceived e-readiness model (PERM), actor–network theory (ANT), and the Trans-theoretical model of adoption (TTMA) (Table 2).

4.1.7. Academic landscape

To provide a strong overview of the academic landscape of the included study, we identified the most frequently represented journals, and most cited articles. Table 3 presents the top five journals by publication count and most cited studies. *Smart Agricultural Technology* was the most frequently represented journal, with 11 included studies, followed by *Sustainability* (n = 6), *Precision Agriculture* (n = 5), *Computers and Electronics in Agriculture* (n = 5), and *Frontiers in Sustainable Food Systems* (n = 4). These five journals accounted for 31 of the 129 included studies (24.03%), indicating that the literature was distributed across a broad range of publication outlets rather than concentrated in a small number of journals. Citation counts were based on the total number of citations reported in Scopus. As 30 of the included studies were not indexed in Scopus, citation rankings were conducted for the remaining 99 studies. The most cited study was *Farm and operator characteristics affecting the awareness and adoption of precision agriculture technologies in the US*, which had received 325 citations.

4.2. Result of systematic review

The systematic review synthesized determinants that were explicitly associated with one or more adoption constructs in the original studies. In quantitative studies, both focal predictors and control variables were included when a direct statistical association with WTA, BI, or UB was reported. In qualitative studies, determinants were included when authors explicitly identified them as facilitating or constraining willingness, intention, or actual technology use. Mediating variables and indirect pathways were not included in the synthesis. The most frequently reported determinants across the included studies are summarized in Table 4. Definitions of the determinants are presented in Appendix G.

4.2.1. Willingness to adopt

Evidence on WTA was comparatively limited. Studies examined socio-demographic and farm characteristics, but economic considerations were also prominent, particularly technology cost and perceived benefits. Technology cost (n = 9) was the most frequently investigated determinant outside demographic and farm characteristics and was consistently associated with lower willingness. Perceived benefits

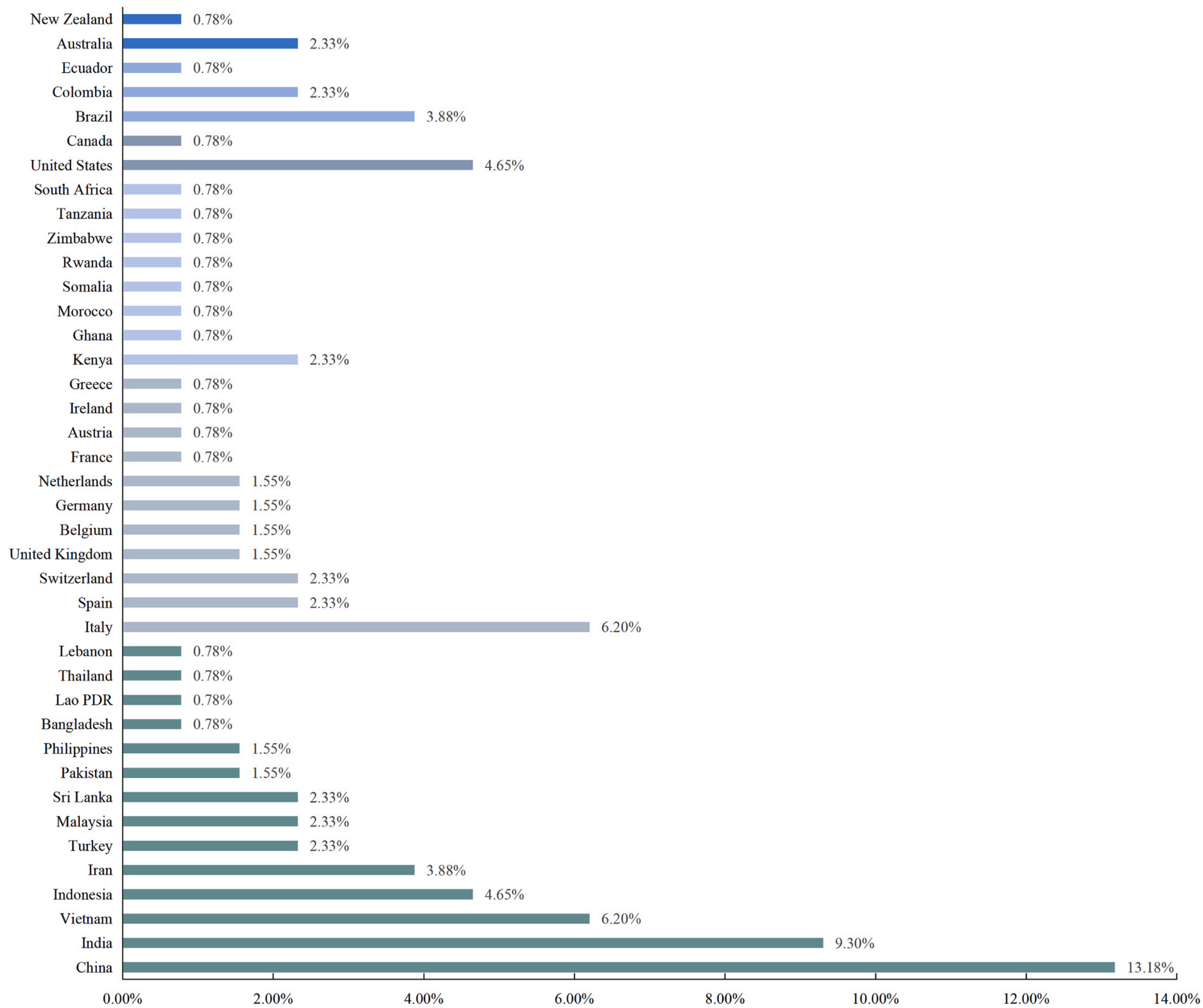

Fig. 3. Geographical distribution of 129 included studies.

(n = 4) were generally positively associated with WTA but were examined in relatively few studies.

4.2.2. *Behavioral intention*

BI was primarily examined through psychological and social determinants. Perceived ease of use (n = 15), social influence (n = 15), perceived usefulness (n = 13), and attitude toward technology (n = 10) were the most frequently investigated determinants. Perceived usefulness and attitude toward technology were generally positively associated with BI, whereas findings for perceived ease of use and social influence were more mixed. These determinants were commonly examined within psychological adoption frameworks, particularly the TAM and TPB.

4.2.3. *Usage behavior*

UB was investigated across the broadest range of determinants. Compared with WTA and BI, studies of actual technology use examined a wider range of technical, knowledge, social, infrastructure, and institutional determinants alongside socio-demographic and farm characteristics. Technology cost (n = 40) was the most frequently investigated factor and was consistently associated with lower technology use. Government support (n = 27), perceived benefits (n = 22), and digital knowledge or awareness (n = 22) were generally associated with greater technology use. Findings for digital infrastructure (n = 25) and training participation (n = 22) varied across studies. High investment, maintenance, and repair costs were frequently reported as barriers to technology use, particularly for small and medium sized horticultural enterprises [84]. Government incentives, technical assistance, and supplier support were commonly reported as facilitating technology use [85–87]. By contrast, findings for credit access and digital infrastructure were mixed across studies, suggesting that financial resources and connectivity did not show consistent relationships with actual technology use across horticultural contexts [88,89].

4.2.4. *Determinants across adoption constructs*

Across all adoption constructs, socio-demographic and farm characteristics, including age, education level, farming experience, planting area, and farm labor size, were among the most frequently examined variables. However, these variables showed mixed directions of association across studies, suggesting that their association with DT adoption are context-dependent rather than universal.

4.3. *Result of meta-analysis*

4.3.1. *Meta-analysis*

For the quantitative synthesis, only determinants examined in at least five studies were included. WTA was not included because too few studies reported comparable quantitative data. Separate random effects models were estimated for determinants associated with BI and UB. Pooled effect sizes, 95% confidence intervals, and heterogeneity statistics are reported in Table 5.

For BI, four determinants showed statistically significant pooled

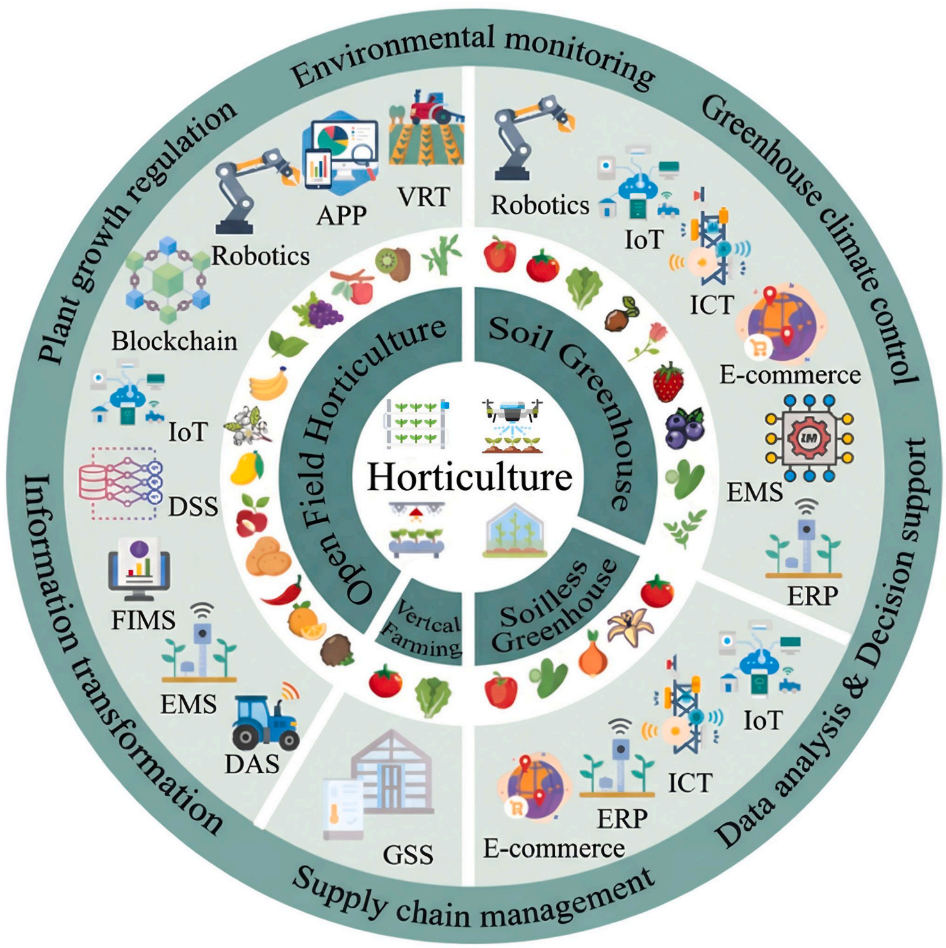

Fig. 4. Overview of the digital technologies per crop system. Credit: Authors' construction using icons from Flaticon.com.
Legend: VRT = variable rate technology; DSS = decision support systems; FIMS = farm information management systems; EMS = electronic measuring systems; DAT = driver assistance systems; GSS = growing-service systems; ERP = enterprise resource planning system; IoT = Internet of Things; ICT = information and communications technology.

Table 2
Types of theoretical framework reported in the included studies.

Theoretical framework	Number of studies	Studies
Technology acceptance model (TAM)	17	[44–60]
Diffusion of innovations (DOI)	11	[45,55,58,59,61–67]
Technology organization environment framework (TOE)	8	[45,57,64,66,68–71]
Theory of planned behavior (TPB)	5	[58,67,72–74]
Unified theory of acceptance and use of technology (UTAUT)	5	[59,70,71,75,76]
Technology acceptance model 3 (TAM3)	2	[77,78]
Unified theory of acceptance and use of technology 2 (UTAUT2)	2	[79,80]
Behavioral reasoning theory (BRT)	2	[81,82]
Resource based view (RBV)	1	[45]
Theory of herd behavior (THB)	1	[56]
Perceived e readiness model (PERM)	1	[68]
Actor network theory (ANT)	1	[65]
Transtheoretical model of adoption (TTMA)	1	[83]

associations. Age was negatively associated with intention (ES = −0.115, p = 0.021), whereas social influence (ES = 0.295, p = 0.002), perceived usefulness (ES = 0.373, p < 0.001), and perceived ease of use (ES = 0.167, p < 0.001) showed statistically significant effects. For UB, nine of the fifteen pooled determinants were statistically significant. Positive pooled associations were observed for sex (ES = 0.123, p = 0.003), education level (ES = 0.170, p < 0.001), training participation (ES = 0.196 p < 0.001), planting area (ES = 0.123, p = 0.002), farming income (ES = 0.328, p = 0.013), household income (ES = 0.187, p = 0.004), organization/cooperative membership (ES = 0.134, p = 0.023), risk attitude (ES = 0.122, p = 0.024), and social influence (ES = 0.246, p < 0.001). The most statistically significant pooled effects were small to moderate in magnitude. Heterogeneity varied considerably across the pooled estimates. High heterogeneity, defined as $I^2 \geq 75\%$, was observed for 13 of the 21 pooled estimates, including three of the six BI estimates and 10 of the 15 UB estimates.

4.3.2. Subgroup analysis of determinants of usage behavior

To explore potential sources of heterogeneity, subgroup analyses were conducted for UB determinants examined in at least ten independent studies and showing substantial heterogeneity ($I^2 \geq 75\%$). Five determinants met these criteria: age, sex, education level, planting area, and training participation. Table 6 presents subgroup analyses with statistically significant differences across subgroups, while the complete results are provided in Appendix H.

Significant differences by geographic region were observed for sex (Q = 16.441, p(Q) < 0.001), education level (Q = 7.368, p(Q) = 0.025), and training participation (Q = 11.262, p(Q) = 0.004). Training participation also differed significantly across DT types (Q = 12.010, p

Table 3
Top five journals by publication count and the five most cited studies.

Rank	Journal	Journal article count	Rank	Title	Total citations
1	Smart Agricultural Technology	11	1	Farm and Operator Characteristics Affecting the Awareness and Adoption of Precision Agriculture Technologies in the US	325
2	Sustainability	6	2	Analysis of Blockchain's enablers for improving sustainable supply chain transparency in Africa cocoa industry	162
3	Precision Agriculture	5	3	Precision agriculture technology adoption: a qualitative study of small-scale commercial "family farms" located in the North China Plain	129
3	Computers and Electronics in Agriculture	5	4	Smart farming technology innovations – Insights and reflections from the German Smart-AKIS hub	116
4	Frontiers in Sustainable Food Systems	4	5	Status quo of adoption of precision agriculture enabling technologies in Swiss plant production	100

Note: Citation counts were based on the total number of citations reported in Scopus as of July 2026.

Table 4
Frequency and reported direction of determinants associated with willingness to adopt (WTA), behavioural intention (BI), and usage behaviour (UB).

Category of determinants	Determinants	WTA	BI	UB	Observed direction
Socio-demographic characteristics	Age	7	9	36	±
	Sex	3	7	22	±
	Education level	6	9	39	±
	Farming experience	3	2	16	±
Farm characteristics	Planting area	6	6	38	±
	Farm labor size	4	2	20	±
	Farming income	2	0	9	+
	Household income	1	2	9	±
	Organization/ cooperative membership	2	0	11	+
	Farm capital	1	0	10	+
	Geographic location	5	1	5	±
	Distance to market	0	1	7	±
Knowledge and capability determinants	Training participation	3	2	22	±
	Human resources capacity	0	1	9	+
	Digital knowledge/ awareness	2	5	22	+
	Digital skills	0	2	16	+
Technical determinants	Operational benefits	2	0	11	+
	Technology cost	9	4	40	-
	Technology availability	0	2	10	+
	Technology compatibility	1	4	18	+
	Technology complexity	1	2	14	-
	Technology readiness	0	2	8	+
	Relative advantage	1	1	7	+
Psychological determinants	Perceived usefulness	1	13	10	+
	Perceived ease of use	1	15	12	±
	Attitude toward technology	2	10	9	+
	Perceived benefits	4	6	22	+
	Trust in technology	1	2	12	+
	Effort expectancy	2	6	2	±
	Performance expectancy	1	6	3	+
	Risk attitude	0	3	10	+
Social and economic determinants	Information access	2	1	13	±
	Social networks	3	0	9	±
	Social influence	3	15	13	±
	Credit access	2	1	14	±
Infrastructure determinants	Digital infrastructure	2	2	25	±
	Basic infrastructure	2	0	9	+
	Facilitating conditions	1	8	2	±
Institutional determinants	Extension support	1	2	12	+
	Technical assistance	1	1	12	+
	Government support	3	5	27	+

Note: "+" = positive association, "−" = negative association, "±" = both positive and negative associations were reported.

(Q) = 0.001) and crop systems (Q = 29.406, p(Q) < 0.001). For planting area, significant differences were observed across DT types (Q = 8.884, p (Q) = 0.012). No significant subgroup differences were identified for age. Individual subgroup estimates based on one or two studies should be interpreted cautiously; these estimates are reported to reflect the distribution of the available evidence.

4.3.3. Publication bias and sensitivity analysis

Publication bias was assessed using funnel plots and Egger's regression tests (Appendix I). For BI, Egger's tests showed no significant asymmetry for most determinants, except for education level ($p = 0.043$). However, given the small number of studies available for each determinant, these results were interpreted cautiously and were not considered conclusive evidence of publication bias. For UB, significant funnel-plot asymmetry was identified for sex ($p = 0.014$) and education level ($p = 0.030$), consistent with visual inspection of the corresponding funnel plots.

Funnel-plot asymmetry may reflect publication bias, small-study effects, or residual heterogeneity. To examine the robustness of the pooled estimates, trim-and-fill analyses were performed [90]. For sex, no studies were imputed and the pooled effect remained unchanged. For education level, two studies were imputed, reducing the pooled effect from 0.170 to 0.150. Although these adjustments modestly affected effect size magnitude, they did not alter the direction or statistical significance of the principal findings.

Sensitivity analyses were conducted by repeating the meta-analyses after excluding studies with MMAT scores below 60% (Appendix J). Most pooled estimates remained similar in direction to those obtained in the primary analyses. However, the statistical significance of several pooled associations has changed. Age became significantly negatively associated with UB, while farming experience became significantly positively associated with UB. In contrast, household income, risk attitude, and social network were no longer significantly associated with UB.

5. Discussion

This review synthesized evidence from 129 empirical studies to

Table 5
Pooled random-effects meta-analysis of determinants associated with behavioural intention (BI) and usage behaviour (UB).

Variable	k	ES	[95% CI]	Z	p	Tau^2	Q-value	p (Q)	I^2 (%)
BI									
Age	7	−0.115	[-0.211, −0.017]	−2.301	0.021	0.116	28.576	0.000	79.003
Education level	6	0.051	[-0.037, 0.138]	1.130	0.258	0.092	17.664	0.003	71.693
Planting area	5	0.060	[-0.049, 0.168]	1.081	0.280	0.103	13.669	0.008	70.736
Social influence	5	0.295	[0.110, 0.460]	3.083	0.002	0.208	43.532	0.000	90.811
Perceived usefulness	6	0.373	[0.230, 0.499]	4.883	0.000	0.186	51.731	0.000	90.335
Perceived ease of use	6	0.167	[0.124, 0.209]	7.526	0.000	0.000	2.050	0.842	0.000
UB									
Age	20	−0.019	[-0.083, 0.046]	−0.567	0.571	0.127	119.192	0.000	84.059
Sex	14	0.123	[0.041, 0.202]	2.957	0.003	0.137	95.679	0.000	86.413
Education level	22	0.170	[0.112, 0.226]	5.707	0.000	0.117	110.174	0.000	80.939
Farming experience	12	0.041	[-0.018, 0.099]	1.370	0.171	0.075	30.164	0.001	63.532
Training participation	11	0.196	[0.100, 0.288]	3.974	0.000	0.150	96.145	0.000	89.599
Farm labor size	14	0.048	[-0.012, 0.107]	1.553	0.120	0.091	49.662	0.000	73.823
Planting area	19	0.123	[0.047, 0.197]	3.166	0.002	0.154	170.163	0.000	89.422
Farming income	5	0.328	[0.073, 0.544]	2.491	0.013	0.286	32.599	0.000	87.729
Household income	6	0.187	[0.060, 0.308]	2.878	0.004	0.147	43.647	0.000	88.544
Organization/cooperative membership	6	0.134	[0.019, 0.246]	2.279	0.023	0.131	35.516	0.000	85.922
Risk attitude	5	0.122	[0.016, 0.224]	2.263	0.024	0.096	13.585	0.009	70.555
Social network	6	0.051	[0.008, 0.093]	2.349	0.019	0.030	7.332	0.197	31.810
Social influence	5	0.246	[0.175, 0.314]	6.636	0.000	0.062	9.948	0.041	59.792
Credit access	7	−0.082	[-0.224, 0.063]	−1.111	0.267	0.183	68.071	0.000	91.186
Distance to market	6	0.068	[-0.104, 0.235]	0.772	0.440	0.198	41.457	0.000	87.939

Legend: k = number of original studies that used each determinant; ES = pooled effect size; p = p-value of meta-analysis; Z = z-value of meta-analysis; 95%CI = 95% confidence interval; Q = value of Q-statistic; p(Q) = p-value of Q-statistic; I^2 = scale-free index of heterogeneity; BI = behavioral intention; UB = usage behavior.

Table 6
Subgroup analyses for moderators showing significant between-group differences.

Variable	Moderator	Subgroup	k	ES	[95% CI]	p	Q	df	P (Q)
Sex	Geographical region	Africa	1	0.416	[0.283, 0.533]	0.000	16.441	2	0.000
		Asia	12	0.091	[0.015, 0.167]	0.020			
		North America	1	0.147	[-0.081, 0.361]	0.206			
Education level	Geographical region	Africa	1	0.151	[0.000, 0.295]	0.049	7.368	2	0.025
		Asia	19	0.152	[0.092, 0.210]	0.000			
		North America	2	0.382	[0.227, 0.519]	0.000			
Training participation	Geographical region	Asia	9	0.218	[0.116, 0.316]	0.000	11.262	2	0.004
		Europe	1	−0.081	[-0.232, 0.074]	0.305			
		North America	1	0.258	[0.035, 0.457]	0.024			
	DT types	DTC	9	0.228	[0.126, 0.325]	0.000	12.010	1	0.001
		DTP and DTC	2	0.016	[-0.046, 0.077]	0.622			
	Crop systems	Mixed production systems	1	0.456	[0.338, 0.560]	0.000	29.406	3	0.000
		Not specific	3	0.236	[0.039, 0.416]	0.019			
		Open field horticulture	6	0.174	[0.052, 0.290]	0.005			
		Soilless greenhouse	1	−0.081	[-0.232, 0.074]	0.305			
Planting area	DT types	DTC	12	0.045	[-0.020, 0.110]	0.170	8.884	2	0.012
		DTP	5	0.264	[0.092, 0.420]	0.003			
		DTP and DTC	2	0.154	[0.093, 0.213]	0.000			

Legend: ES = pooled effect size; DTC = digital technologies of communication; DTP = digital technologies of production; multiple stakeholders include growers, contractors, commission agents, wholesalers, crop food processors, exporters, experts, agricultural technology firms, government organizations, R&D organizations, and GNO; Q tests differences in pooled effects across subgroups; p (Q) is the associated p-value, p(Q) < 0.05 indicates a significant moderator effect.

examine how digital technology (DT) adoption has been investigated in horticulture. Rather than demonstrating a universal sequence of adoption, the combined systematic review and meta-analysis reveal an uneven evidence base across adoption constructs, DT types, crop systems, and geographical regions. Three broader patterns emerge from the findings: research is concentrated in specific regions and production systems; determinants differ across willingness to adopt (WTA), behavioral intention (BI), and usage behavior (UB); and the observed associations with actual technology use are highly context dependent.

5.1. An uneven evidence base

The review demonstrates that the current evidence base is unevenly distributed across geographical regions, crop systems, and DT types. Studies from Asia and Africa predominantly investigate relatively accessible communication technologies associated with urgent market access and climate adaptation needs [91], including mobile applications, e-commerce platforms, and ICT-based advisory services, whereas studies from Europe and other high-income regions more frequently examine capital-intensive production technologies such as robotics, drones, and sensor-based automation to offset high labor costs [92]. This geographical pattern is consistent with broader agricultural innovation literature, which shows that technology development often reflects differences in labor availability, production constraints, infrastructure, and investment capacity [93,94].

Crop systems are similarly unevenly represented. Open-field horticulture dominates the literature [95], while protected cultivation systems, including soil-based greenhouses, soilless greenhouse production, and vertical farming, remain comparatively underrepresented despite their high potential for digital integration. This imbalance suggests that some of the most technologically intensive horticultural systems have received relatively limited attention within adoption research.

The methodological profile of the literature further reinforces this unevenness. Most studies relied on quantitative designs, whereas mixed methods of approach remained relatively uncommon. This methodological emphasis enables researchers to identify statistical associations but provides more limited insight into the mechanisms and contextual conditions underlying these relationships. As a result, existing research is less well equipped to explain why the associations between similar determinants and DT adoption vary across contexts or how adoption decisions evolve over time. Literature is also unevenly distributed across the three adoption constructs. Most studies examined UB, fewer investigated BI, and relatively few focused on WTA. This imbalance restricts empirical understanding of whether, and under what conditions, WTA and BI are associated with subsequent technology use. These methodological and conceptual gaps indicate that future research would benefit from longitudinal and mixed methods designs that examine relationships among WTA, BI, and UB within broader social, technical, and institutional contexts.

5.2. Adoption differs across analytical constructs

Different categories of determinants were emphasized depending on whether studies examined willingness, intention, or actual technology use, with substantially more evidence available for UB and BI than for WTA.

Because relatively few studies investigated WTA and comparable quantitative evidence was insufficient for meta-analysis, conclusions regarding this construct should be interpreted cautiously. The existing literature suggests that growers often evaluate technical cost and benefits before forming more concrete adoption intentions, particularly in a sector characterized by substantial investment requirements and production uncertainty [51].

Studies of BI predominantly examine psychological determinants. Perceived usefulness, perceived ease of use, and social influence are the most frequently reported determinants, consistent with the emphasis of frameworks such as the TAM and the TPB. For example, Doanh et al. [60] showed that limited understanding of the operational benefits of live-streaming technologies reduced both perceived usefulness and perceived ease of use, thereby weakening BI. Several studies operationalize WTA and BI interchangeably, obscuring an important conceptual distinction [96,97]. In the horticulture sector, high technical risks and investment costs make this distinction especially relevant.

By contrast, studies of UB examined a broader range of technical, knowledge, social, infrastructure, and institutional determinants. Government support, perceived benefits, and digital knowledge or awareness was frequently associated with greater technology use, whereas findings for digital infrastructure varied across studies. Previous research similarly indicates that actual technology use is associated not only with individual perceptions and intentions but also with facilitating conditions, resources, knowledge, and broader structural conditions [98–100]. These patterns indicate that UB was studied more often in relation to knowledge, resources, technical support, and enabling institutional conditions than to psychological determinants alone. The importance of these conditions may help explain why favorable intentions toward DTs do not always correspond with their use in practice [101].

5.3. Contextual variation in determinants of usage behavior

The meta-analysis identified several socio-demographic and farm characteristics that were significantly associated with UB, broadly consistent with findings from previous reviews [102–105]. But the magnitude of these pooled associations varied considerably across studies. The subgroup analyses indicate that the associations between four determinants and UB varied across geographic regions, DT types, and crop systems. These moderators represent different dimensions of the adoption context rather than isolated influences. However, several subgroup estimates were based on only one or two studies, which limit conclusions about the specific mechanisms underlying these differences.

The association between sex and UB differed significantly across regions, indicating that differences between male and female growers were not consistent across geographical contexts. These differences may partly reflect social, regulatory, and cultural conditions that vary across countries and shape women's opportunities to engage with agricultural technologies [106,107]. Higher education was generally positively associated with UB and may provide a stronger cognitive foundation for engaging with DTs [108,109], but the magnitude of this association varied across regions and should be interpreted within the broader conditions shaping technology use. Participation in training is an important condition for farmers to acquire the knowledge and skills needed to adopt DTs, but it does not necessarily translate into greater technology use. Regional differences in infrastructure and extension support, different skill requirements across crop systems, and variation in technology complexity may all shape the strength of this association. The pooled association between planting area and UB also varied significantly across DT types. The association was significant for DTP but not for DTC, possibly because production technologies generally require greater capital investment, equipment integration, and scale related resources [110].

5.4. Theoretical contributions

Compared with previous reviews of agricultural digitalization, this study contributes by providing a more differentiated understanding of DT adoption in horticulture. First, the findings show that the horticultural context matters when interpreting DT adoption. The associations between several determinants and technology use varied across geographic regions, DT types, and crop systems, indicating that adoption determinants do not operate uniformly across horticultural contexts. This suggests that production and technological contexts should be considered when applying general technology adoption theories to horticulture [111,112].

Second, the review introduces WTA, BI, and UB as an analytical classification framework for organizing heterogeneous empirical evidence rather than as a universally validated behavioral sequence. This framework enables studies using different theoretical perspectives and construct measures to be synthesized within a common structure while maintaining a conceptual distinction between willingness, intention, and actual technology use. Treating these constructs as separate analytical categories also makes it possible to examine the extent to which willingness and intention translate into actual use, thereby highlighting the potential decoupling between psychological readiness and technology adoption in practice.

Third, the findings suggest that existing adoption theories provide complementary rather than competing perspectives. Theories such as TAM and TPB (e.g., perceived usefulness, ease of use, attitudes) predominantly inform studies of BI, whereas organizational frameworks such as TOE (e.g., technical costs, government support, technical readiness) more frequently appear in studies examining implementation and actual technology use. Rather than identifying a single superior theory, the review indicates that different theoretical perspectives illuminate different dimensions of horticultural digitalization.

5.5. Practical implications

The findings have practical implications for multiple stakeholder groups involved in horticultural digitalization. For growers, training opportunities and knowledge development are particularly important for supporting technology implementation, especially where digital skills remain limited. Such support can improve growers' digital knowledge and understanding of DTs, helping them better evaluate their usefulness and apply them effectively in practice. For technology developers, the findings highlight the importance of user-friendly and cost-effective solutions design [102]. Technologies should be easy to understand and operate, compatible with diverse production systems, and designed to minimize unnecessary complexity. These features can improve perceived ease of use and make DTs more accessible to a wider range of users. For policymakers, reducing financial barriers alone is unlikely to be sufficient. Government support, technical assistance, and enabling infrastructure to appear frequently alongside actual technology use, suggesting that coordinated implementation strategies may be more effective than isolated subsidy programs. It is also suggested that a range of appropriate approaches should be developed to demonstrate the practical advantages of DTs to farmers and encourage their adoption [113].

5.6. Limitations and future research

Several limitations should be considered when interpreting these findings. First, evidence on WTA remains comparatively limited. The number of studies reporting comparable quantitative data was insufficient for meta-analysis, and conclusions regarding this construct therefore rely primarily on the systematic synthesis rather than pooled quantitative estimates. Second, substantial heterogeneity characterized many pooled estimates. Although random effects models and subgroup analyses were used to examine this variability, the pooled estimates should be interpreted as average associations across highly diverse contexts rather than universal effect sizes. Third, some subgroup estimates were based on only one or two studies, particularly within certain geographic regions, DT types, and crop systems. Although significant moderator effects were identified, estimates for these individual subgroups may be unstable and should therefore be interpreted cautiously. Sensitivity analyses excluding studies of lower methodological quality showed that most associations remained similar in direction, although the statistical significance of several determinants changed. Fourth, despite comprehensive database searches and supplementary strategies (e.g., Google Scholar and conference proceedings), there is the potential omission of unpublished studies and selective reporting bias, although funnel plot, Egger's test, and trim-and-fill procedures were applied to mitigate this risk.

Fig. 5 summarizes how determinants are distributed across the literature examining WTA, BI, and UB. It reflects patterns observed in the reviewed evidence rather than a universally established sequential adoption pathway. Studies of BI placed greater emphasis on psychological and social determinants, whereas studies of UB examined a broader range of technical, knowledge, social, infrastructure, and institutional determinants. Evidence on WTA remained comparatively limited, with technology cost and perceived benefits receiving particular attention. Variation across geographic regions, crop systems, and DT types further indicates that the determinants associated with adoption differ across horticultural contexts, challenging the assumption that a single pattern can adequately represent DT adoption in horticulture or agriculture more broadly.

6. Conclusion

Digital technology (DT) adoption in horticulture is often treated as a

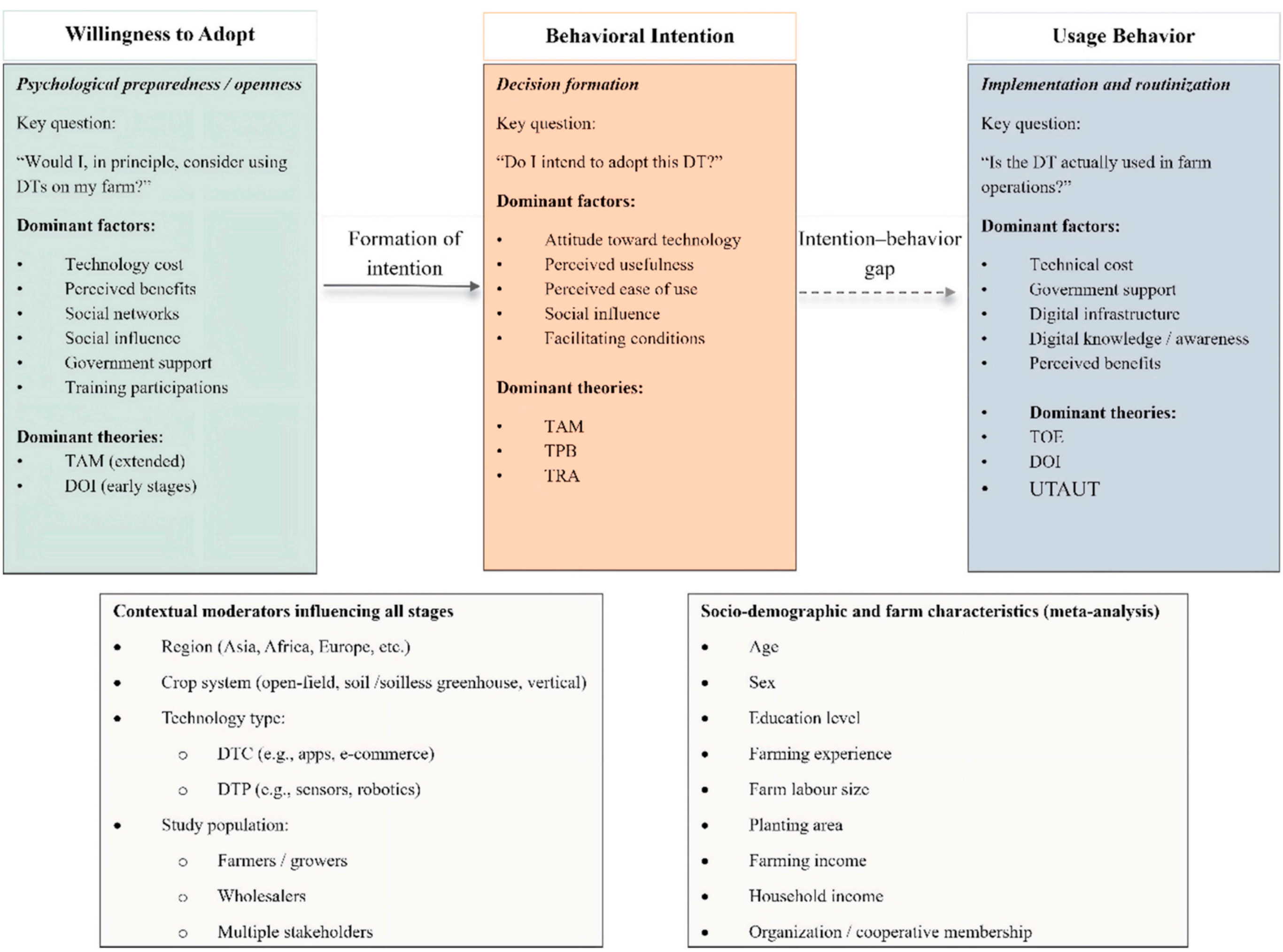

Fig. 5. Analytical synthesis of adoption constructs and dominant determinants reported across the horticultural digital technology adoption literature.

binary choice between adoption and non-adoption, overlooking its heterogeneous and context dependent nature. By combining a systematic review with quantitative meta-analysis, this study provides the first horticulture specific synthesis across three analytically distinct adoption constructs: willingness to adopt (WTA), behavioural intention (BI), and usage behaviour (UB).

The distribution of determinants differed across WTA, BI, and UB. Studies of BI focused mainly on psychological and social determinants, whereas studies of UB examined a broader range of technical, knowledge, social, infrastructure, and institutional determinants. Evidence on WTA was more limited, with technology costs and perceived benefits among the more frequently examined determinants. These patterns reflect differences in the current evidence base rather than a universal sequence of DT adoption. The meta-analysis further demonstrates that socio-demographic and farm-level characteristics interact with geographical region, crop systems, and DT types, indicating that no single predictor consistently explains digital technology adoption across horticultural contexts.

This review contributes to the literature by distinguishing WTA, BI, and UB as separate adoption constructs and by showing that the determinants associated with DT adoption differ across these constructs and horticultural contexts. It also demonstrates that existing adoption theories provide complementary perspectives rather than a single universal explanation of technology adoption. These findings have practical implications for researchers, policymakers, and practitioners seeking to promote DTs uptake in horticulture. Lower barrier communication technologies may benefit from greater awareness, knowledge, and perceived usefulness, whereas capital intensive production technologies require stronger institutional, technical, financial, and infrastructural support. Tailoring interventions to the adoption construct being addressed may therefore contribute to more effective and context-sensitive digitalization strategies within horticultural production systems.

CRediT authorship contribution statement

Wenxuan Geng: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Junye Zhao:** Supervision, Project administration, Funding acquisition, Conceptualization. **Laurens Klerkx:** Writing – review & editing. **Marinus van Haaften:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

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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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jafr.2026.103253.

Data availability

Data will be made available on request.

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