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Review

Toward Sustainable Mechanized Production of Processing Tomatoes: Crop–Machine Interactions, Operational Trade-Offs, and Pathways for Intelligent Control

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Abstract

Mechanized production of processing tomatoes depends on coordinated operations, but crop variability and successive material transfers make performance strongly condition-dependent. This narrative review used structured, non-systematic literature identification across multidisciplinary databases and publisher platforms, supplemented by backward reference tracing through July 2026. Evidence was synthesized through crop–agronomy conditions, machine responses, operational trade-offs, validation maturity, sustainability-related outcomes, and downstream residue requirements. Four findings emerge. First, architecture, maturity synchronization, fruit mechanics, stand geometry, and water status define machine operating envelopes. Second, harvesting is governed by a persistent conflict among detachment, loss, damage, impurity content, throughput, and energy demand; comparisons of settings benefit from a common basis in cultivar, feed rate, machine configuration, and metric definition. Third, sensing and prediction studies provide a foundation for automatic execution and feedback-based adjustment, with replicated whole-machine field trials offering the next step in evaluating multistage control. Fourth, residue discharge, size reduction, collection, and densification need to be specified backward from soil-incorporation or valorization requirements. Operation-specific sustainability benefits are most directly supported for water and input efficiency, marketable-yield retention, and residue recovery, with matched assessments of energy, cost, and life-cycle impacts providing opportunities to extend these findings. Progress therefore requires crop-specific tests that report engineering benefits together with losses, adverse effects, resource use, and operating boundaries.

Keywords: processing tomato; agricultural machinery; crop–machine interaction; low-damage harvesting; closed-loop control; residue valorization

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1. Introduction

Mechanized production of processing tomato is governed by crop–machine interaction, defined here as the condition-dependent coupling between crop and field states and the design, settings, and mechanical actions of equipment. The concept has three linked attributes. Its conceptual attribute identifies which crop traits and agronomic conditions interact with a machine and through which mechanism. Its performance attribute explains how that interaction changes measurable outcomes such as feeding stability, detachment, loss, damage, impurity content, throughput, and energy demand. Its decision-support attribute translates observed crop, field, and material-flow states into choices of machine

configuration, operating parameters, or control actions. This definition is the analytical convention adopted in this review. Its crop-side basis includes managed flowering and harvest timing in processing tomato [1], fruit load response [2–6], and genetic regulation of reproductive development [7]; greenhouse peduncle-pose estimation illustrates geometric sensing for a different harvesting context [8]. Together, these studies contribute crop-development and sensing insights to the framework; integrated evaluation could further connect these elements with machine performance.

The analytical framework in Figure 1 follows a directional chain: crop traits and agronomic conditions → mechanical challenges → engineering responses → operational performance → production and sustainability outcomes. Architecture, maturity distribution, fruit–pedicel attachment, mechanical resistance, stand geometry, soil condition, and water status can create challenges in trafficability, alignment, feeding, separation, cleaning, impact exposure, and residue handling. Engineering responses include mechanism design, geometric matching, parameter adjustment, sensing, decision rules, actuation, and feedback. This review proposes evaluating these responses through marketable yield, quality, loss, impurities, throughput, resource use, energy demand, and residue circularity. Deficit-irrigation, nutrient, and mycorrhizal experiments in processing tomato describe agronomic responses to specific treatments [9–12], while research on mulch materials addresses installation and end-of-season management [13]. Their implications for downstream machine performance and system-level sustainability require joint agronomic and operational assessment.

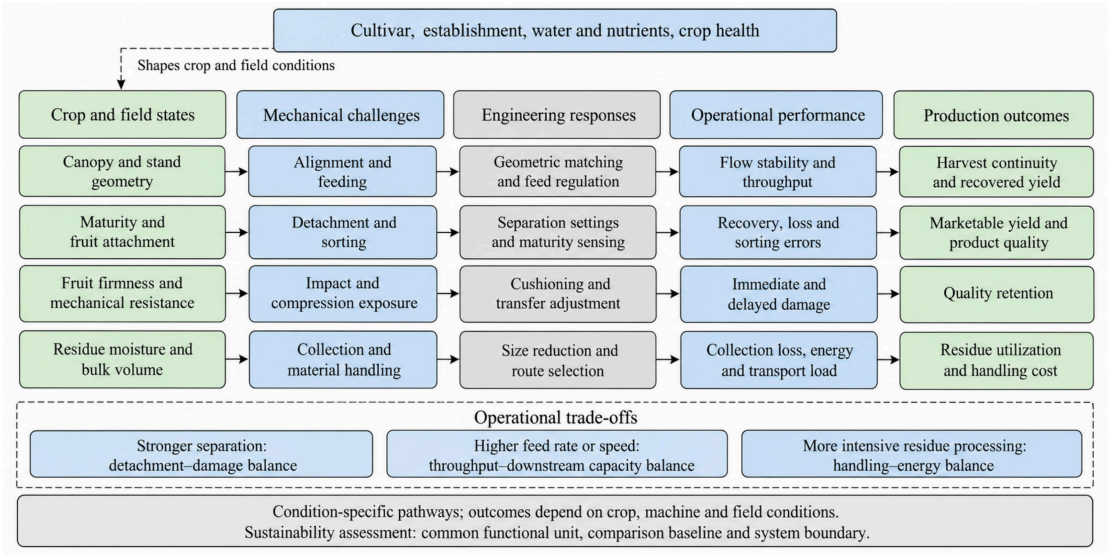


Figure 1. Crop–machine interactions and operational trade-offs across the processing-tomato production chain.The dashed arrow denotes the influence of crop and field management on crop and field states, whereas solid arrows indicate the main progression from crop state through machine response to production outcomes.

Upstream management shapes crop and field conditions relevant to downstream equipment design and operation. Processing-tomato pinching can change flowering and harvest timing [1]; stage-specific irrigation, nitrogen, and mycorrhizal treatments affect yield or resource-use indicators within their tested systems [9–12]; and mulch choice entails agronomic and material-removal trade-offs [13]. Engineering interpretation links crop establishment and stand geometry to alignment and feeding, water management to harvest readiness, and residual film or tape to possible contamination. These proposed links describe how upstream conditions may influence later operations, although joint crop–machine measurements remain necessary to quantify their effects. A mismatch

created during establishment or field management may appear later as unstable feed rate, ineffective separation, excessive cleaning load, fruit damage, harvest loss, or contaminated residues. Tracing these upstream influences alongside the affected component would support a more complete interpretation of downstream performance.

Evidence across the chain includes distinct technologies and verification contexts. Vegetable-transplanting work covers mechanism analysis and laboratory pickup tests [14,15]; proximal optical sensing examines sweet-pepper nitrogen measurements [16]; rice-residue research tests crushing and throwing [17]; combine-cleaning research examines uneven airflow using measurements and numerical modeling [18]; and greenhouse vision detects tomato maturity classes [19]. Weed-recognition research in grain systems provides further sensing evidence [20]. Together, these examples offer complementary methods for developing integrated processing-tomato automation, with each contributing at its own crop and validation scale. Performance gains are also conditional: higher travel speed can increase throughput but destabilize feeding; stronger separation or cleaning can reduce retained fruit or impurities while increasing collision exposure, damage, or loss; and more intensive residue size reduction can facilitate downstream use while increasing energy demand. Rice-loss sensing provides a measurement example [21], broad-bean harvesting examines adaptive control [22], and spray-boom active suspension links attitude measurements to electro-hydraulic adjustment [23]. These complementary sensing and control functions support integrated design; crop-specific response measurements can guide their adaptation to processing-tomato operations [6,18,19,24].

Technology-specific contributions include a review of vegetable-transplanter mechanisms [14], laboratory development of a pickup mechanism [15], a grain-system weed-recognition review [20], and reviews of residue machinery, intelligent spraying, maturity detection, and nondestructive quality assessment [25–29]. This review differs from a conventional machinery survey by using the crop–machine interaction chain as its analytical unit and by tracing how conditions, responses, trade-offs, and evidence strength propagate across production stages. It addresses four questions: (1) how crop traits and agronomic conditions create mechanical challenges; (2) which engineering responses and operational trade-offs govern the principal mechanized stages; (3) how far sensing, decision support, actuation, feedback, and closed-loop control have progressed; and (4) how cross-stage coordination affects marketable yield, product quality, resource use, energy demand, and residue circularity. The contribution is a condition-aware framework that connects upstream agronomy with downstream machine performance, distinguishes demonstrated control from isolated sensing or component optimization, and identifies the evidence needed for coordinated and sustainable mechanization.

2. Review Approach

2.1. Review Scope

This article presents a structured critical narrative review of technologies supporting the mechanized production of processing tomatoes. The scope follows the production sequence—from crop suitability and crop establishment through field management, mechanical harvesting, vine-residue handling, and intelligent equipment. Crop–machine interactions, operational trade-offs, evidence maturity, cross-stage coordination, and sustainability-related outcomes are used as the principal analytical perspectives.

The review addresses four questions: (1) how crop traits and agronomic conditions affect mechanization performance; (2) which performance trade-offs occur in the principal mechanized operations; (3) how far sensing, automatic parameter adjustment, and closed-loop control have progressed; and (4) how coordination among agronomy, machinery, harvesting, logistics, and residue handling affects marketable yield, product quality,

resource use, energy demand, and residue circularity. Evidence was evaluated according to its relevance to these questions rather than for the estimation of a single pooled effect.

2.2. Search Strategy

The primary literature search covered January 1999 through July 2026. Because some studies on early mechanized processing-tomato production, conventional mechanical harvesting, and foundational equipment technologies predate this period, earlier seminal studies or technical reports were selectively included when they provided key information on mechanized operating methods, operating losses, or equipment adaptability.

Thematic search coverage was organized around tomato production and conditionally transferable engineering evidence. Tomato-focused terms encompass crop architecture and material properties, crop establishment, field management, harvesting and handling, residue use, and sensing or control. Separate engineering terms cover seedling handling, combine-harvester operations, residue machinery, and control methods in other systems. This separation allows agronomic studies without a mechanization keyword and cross-crop studies without a tomato keyword to contribute relevant evidence.

The following complete query specifications make this thematic scope explicit for each source. They are formulations based on the cited literature, rather than verbatim records of the original query executions. The stated publication window is January 1999 to July 2026; the endpoint is a publication-coverage limit, not a search-execution date. Earlier foundational studies remain eligible through reference tracing. Quotes denote phrases, OR combines alternatives, AND connects concepts, and parentheses group Boolean clauses. A trailing asterisk is used only in the Web of Science and Scopus formulations to capture word variants.

Web of Science Core Collection: TS specifies the Topic field, covering titles, abstracts, author keywords, and Keywords Plus. The two branches distinguish tomato-focused evidence from transferable engineering studies. The complete advanced-search expression is:

TS = ((tomato* OR “Solanum lycopersicum” OR “Solanum lycopersicon”) AND (mechaniz* OR mechanis* OR harvest* OR transplant* OR “plug seedling” OR tillage OR “drip tape” OR mulch OR weed* OR irrigat* OR fertigat* OR spray* OR monitor* OR “plant architecture” OR firmness OR ripen* OR “mechanical properties” OR sorting OR bruis* OR residue* OR compost* OR “anaerobic digestion” OR “machine vision” OR “deep learning”)) OR TS = ((“plug seedling” OR “combine harvester” OR “crop residue” OR straw OR “agricultural machinery”) AND (picking OR feeding OR threshing OR cleaning OR chopping OR baling OR “end effector” OR “path tracking” OR “adaptive control” OR “closed-loop control”))

Scopus: TITLE-ABS-KEY specifies titles, abstracts, and keywords. The complete advanced-search expression is:

TITLE-ABS-KEY ((tomato* OR “Solanum lycopersicum” OR “Solanum lycopersicon”) AND (mechaniz* OR mechanis* OR harvest* OR transplant* OR “plug seedling” OR tillage OR “drip tape” OR mulch OR weed* OR irrigat* OR fertigat* OR spray* OR monitor* OR “plant architecture” OR firmness OR ripen* OR “mechanical properties” OR sorting OR bruis* OR residue* OR compost* OR “anaerobic digestion” OR “machine vision” OR “deep learning”)) OR TITLE-ABS-KEY ((“plug seedling” OR “combine harvester” OR “crop residue” OR straw OR “agricultural machinery”) AND (picking OR feeding OR threshing OR cleaning OR chopping OR baling OR “end effector” OR “path tracking” OR “adaptive control” OR “closed-loop control”))

ScienceDirect: the specification uses the advanced-search field for title, abstract, or author-specified keywords. Five short expressions are listed separately to avoid an exces-

sively long Boolean query; each contains no more than eight Boolean connectors. Each expression is complete and does not require substitution of an undefined term block:

SD1: tomato AND (mechanization OR mechanisation OR harvesting OR transplanting OR tillage OR "drip tape" OR "mulch laying")

SD2: tomato AND (firmness OR ripening OR "plant architecture" OR irrigation OR fertigation OR spraying OR monitoring)

SD3: tomato AND ("machine vision" OR "deep learning" OR sorting OR bruising OR residue OR composting OR "anaerobic digestion")

SD4: ("plug seedling" OR straw OR "combine harvester") AND (picking OR cleaning OR threshing OR chopping OR baling)

SD5: "agricultural machinery" AND ("end effector" OR "path tracking" OR "adaptive control" OR "closed-loop control")

SpringerLink: the specification uses the general keyword search, which can match indexed content including full text, rather than a Scopus-style title–abstract–keyword field. The following five expressions are complete keyword queries; title and abstract relevance is assessed during screening:

SL1: tomato AND (mechanization OR mechanisation OR harvesting OR transplanting OR tillage OR "drip tape" OR "mulch laying")

SL2: tomato AND (firmness OR ripening OR "plant architecture" OR irrigation OR fertigation OR spraying OR monitoring)

SL3: tomato AND ("machine vision" OR "deep learning" OR sorting OR bruising OR residue OR composting OR "anaerobic digestion")

SL4: ("plug seedling" OR straw OR "combine harvester") AND (picking OR cleaning OR threshing OR chopping OR baling)

SL5: "agricultural machinery" AND ("end effector" OR "path tracking" OR "adaptive control" OR "closed-loop control")

Google Scholar: short queries use quoted phrases and uppercase OR; adjacent terms supply the required conjunction. No database field tag or truncation operator is assumed. The queries below cover direct tomato evidence and transferable machinery studies, while DOI or exact-title matching supports identification of known publications:

GS1: "processing tomato" "mechanical harvesting"

GS2: tomato "mechanical properties" OR firmness OR ripening

GS3: tomato transplanting OR tillage OR "mulch laying" OR "drip tape"

GS4: tomato weeding OR irrigation OR fertigation OR spraying

GS5: tomato "machine vision" OR "deep learning" OR sorting OR monitoring

GS6: "tomato plant residues" composting OR "anaerobic digestion"

GS7: "plug seedling" "pick-up"

GS8: "combine harvester" cleaning OR threshing OR feeding

GS9: straw chopping OR collection OR baling

GS10: "agricultural machinery" "adaptive control" OR "path tracking"

Source interfaces differ in indexing coverage, phrase matching, and date filters, so these formulations do not imply identical retrieval sets. Publication dates require record-level checking because an interface cannot apply precise monthly boundaries. Citation tracing and exact-title or DOI matching complement keyword queries for foundational crop studies, material assessments, and general methodological sources. Search specifications describe identification routes; evidence transfer and the use of each publication are assessed using the applicability rules in Section 2.3.

Cited publications were matched to the consulted full-text versions using DOI and exact-title information. Evidence extraction retained source-page locations for classifications, methodological details, and reported outcomes.

2.3. Literature Screening Process

All retrieved records were imported into EndNote for centralized management. Duplicate records were first identified using EndNote's automatic deduplication function, followed by manual verification and additional deduplication based on title, authors, publication year, and DOI.

A total of 2471 records were retrieved: 612 from Web of Science Core Collection, 358 from Scopus, 526 from ScienceDirect, 401 from SpringerLink, 448 from Google Scholar, and 126 from other sources. After removal of 583 duplicate records, 1888 records proceeded to title and abstract screening.As database contents are continually updated, search results may differ when the searches are conducted at a later date.

During title and abstract screening, 1426 records that were unrelated to fully mechanized processing-tomato production or lacked transferable technical value were excluded, leaving 462 articles for full-text assessment. At the full-text stage, 71 articles were excluded because of limited relevance to mechanized processing-tomato production or transferable mechanical-action mechanisms, 53 because they lacked sufficient technical or quantitative information, 78 because the full text or necessary information could not be obtained, and 64 during the original full-text screening because qualitative comparison indicated that their research topics and principal findings were similar to those of other publications and that they did not provide distinct evidence relevant to the review questions. This category reflects a qualitative assessment of thematic similarity and contribution to the synthesis; it does not mean that duplicate datasets, experiments, or publications were verified. No numerical similarity threshold was applied. The screening process shown in Figure 2 yielded 196 studies for qualitative synthesis. Following reference replacement and removal of nonessential citations, the final reference list contains 183 entries, a net reduction of 13 references.

For the literature synthesized here, relevance was assessed against the four review questions in Section 2.1. An applicable publication contributes at least one identifiable link: a crop or material state relevant to an operation; a machine mechanism or operating response; a measured performance or resource-use outcome; or a sensing, decision, or control method. Crop-focused evidence includes architecture, seedling integrity, fruit firmness, ripening, or health responses that inform machine adaptation. Residue studies contribute when they describe handling properties, collection or densification requirements, transport and storage, or a specified utilization route. Reviews and methodological publications provide contextual or analytical support and are recorded separately from primary experiments.

Transferable technical value was assessed by identifying a shared mechanical action, measured property, or control task and examining the material state, crop architecture, loading conditions, equipment configuration, and validation environment. Other tomato systems and other crops can supply component principles or evaluation methods; their quantitative settings remain attached to the original test conditions. Adoption of an operating parameter additionally requires correspondence in the relevant material and operating conditions. Mechanism-level evidence can therefore be retained for design discussion while crop-specific performance claims are based on the corresponding measured endpoint.

Information sufficiency was judged according to the intended use of the evidence. A numerical comparison requires an identifiable crop or material, test method and setting, outcome definition, unit, and denominator or comparison basis where applicable. Partially reported measurements were retained with appropriate qualifications when their supported scope was clear. Conceptual, simulation, review, and background sources were assessed for their contributions to mechanisms or context without requiring field-performance data. Publications with no identifiable link to the review questions fell outside the analytical

scope, and inaccessible or inadequately documented findings were not used to substantiate numerical performance claims. Uncertain information was recorded as unresolved rather than supplied by inference. Eligibility was assessed according to relevance to the review questions, technical transferability, and information sufficiency.

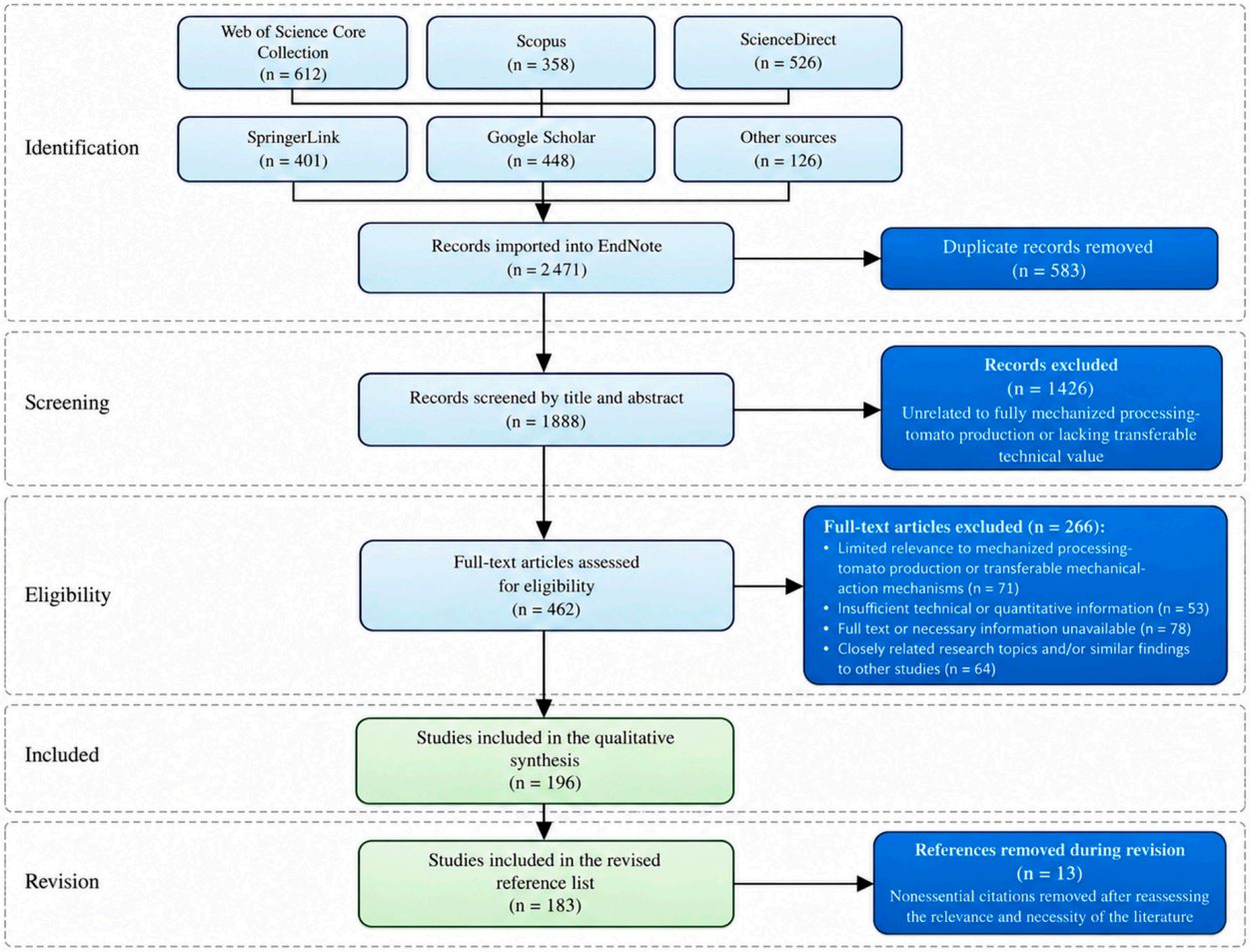


Figure 2. Literature screening flowchart.

DOI and title information were used to identify publications, distinguish duplicate bibliographic records and different versions of the same publication, and separately note possible cases in which distinct publications reported the same experiment. In synthesizing the 183 cited publications, relevance to the review questions, technical transferability, and information sufficiency guided how each source was used. Publications with similar topics or findings were considered separately when differences in crop or cultivar, operating conditions, measured outcomes, or validation settings contributed distinct evidence relevant to the review. These dimensions informed evidence interpretation and were recorded during coding; coding was not a further screening stage. Uncertain versions, units, outcome definitions, or data relationships were documented with appropriate qualifications. The 183 reference-list entries represent cited publications, not a count of independent experiments.

2.4. Evidence Classification

The 183 cited publications were classified by their principal source and validation context. They comprised 114 publications reporting original measurements, 36 primarily concerned with models, algorithms, or concepts, and 33 secondary or background sources.

Five principal evidence categories were applied to the 150 non-secondary publications; secondary sources were retained in a separate group:

(A) whole-machine field tests or commercial-scale operations in processing-tomato production that report mechanical or operational performance;
(B) processing-tomato crop, agronomic, material-property, component, bench, or laboratory measurements, with the measured endpoint identified;
(C) measurements in fresh-market, cherry, protected-culture, or other tomato systems, including tomatoes whose processing use is not specified;
(D) measurements in other crops or transferable engineering systems that inform corresponding mechanical actions, components, measurement methods, or control approaches; and
(E) conceptual or simulation-based evidence, including a separately identified subgroup of physical tests using engineered crop surrogates.

Category A supports interpretation of measured operational performance under the reported crop, machine, and field conditions. Category B contributes crop-specific agronomic, material, or component evidence; its relevance to a subsequent mechanical operation is interpreted through the endpoint actually measured. Categories C and D broaden the available engineering approaches, with material properties, crop architecture, operating loads, and validation conditions guiding transfer to processing tomatoes. Category E supports mechanism exploration and design development, with simulations and physical surrogate tests identified separately. A publication-level category describes its principal evidence contribution; the validation of each stage-specific endpoint is considered separately.

These categories describe evidence provenance and validation scope and were interpreted alongside a separate descriptive appraisal of methodological information. Extraction recorded publication identity, crop and material state, production stage, technology, actual trial or sample-source location, validation environment, scale, operating settings, measured outcomes, and source-page locations. Extracted classifications, units, denominators, and interpretation boundaries were checked against the consulted full texts. These checks provided internal source verification; independent dual-reviewer screening was not undertaken.

The descriptive appraisal covered ten domains: experimental scale (Q1), validation environment (Q2), seasons and locations (Q3), sampling and replication (Q4), comparison design (Q5), validation design and independence (Q6), tested object (Q7), outcome definitions and completeness (Q8), processing-tomato specificity (Q9), and reproducibility information (Q10). Fields were recorded as reported (R), partially reported (PR), unresolved (UV), confirmed not reported (NR), or not applicable (NA), with source locations and interpretation notes. R indicates that information was documented; methodological strength and independence were interpreted from the design itself. No overall quality score was calculated. The domain definitions and aggregate results are presented in Section 2.6.

Each publication received one principal evidence category, publication role, and technology group. Production stages and validation contexts were coded as overlapping labels. Regions were based on trial or sample origins rather than author affiliations, with unspecified locations and secondary sources shown separately. Internal data partitions, additional operating conditions, and tests across seasons or locations were distinguished when interpreting validation. Section 2.6 summarizes the evidence distribution and descriptive appraisal.

2.5. Narrative Synthesis and Claim Boundaries

The included publications were synthesized narratively because substantial heterogeneity existed in cultivar, fruit maturity, crop architecture, soil and field conditions, machine configuration, experimental scale, operating parameters, and definitions of perfor-

mance indicators. The evidence was compared in terms of crop and material characteristics, study scale, machine structure, operating conditions, measured outcomes, and reported limitations. The synthesis emphasized recurring trends, differences among reported results, possible reasons for those differences, conditions of applicability, operational trade-offs, and gaps in direct field validation.

Particular attention was given to the relationships among crop traits, agronomic conditions, machine responses, and downstream performance. Rather than treating individual production stages as independent operations, the analysis considered how variation generated during crop establishment and field management could affect harvesting, separation, cleaning, sorting, transport, and residue handling. Numerical results were interpreted within their original experimental contexts and were used to illustrate condition-dependent performance rather than to rank technologies tested under non-equivalent conditions.

For the assessment of intelligent machinery, the functional control chain was divided into sensing, decision-making, actuation, and feedback. Sensing refers to the acquisition of information on crops, fields, material flow, or machine operating conditions. Decision-making converts the acquired information into an operating recommendation or control target. Actuation implements the corresponding command, whereas feedback evaluates the resulting system response and supports subsequent adjustment. Studies of detection, recognition, prediction, and decision support were classified according to their demonstrated functions; closed-loop evidence additionally included actuation and measured feedback under relevant operating conditions.

The four-part chain describes system functions, with maturity evaluated separately through the scope of validation. Section 8 expands it into sensing, prediction or state estimation, decision, actuation, feedback, and parameter readjustment. The framework distinguishes functions from verification contexts: offline recognition, online detection, decision support, automatic execution, and closed-loop control describe what a system does, whereas whole-machine field validation and cross-stage coordination describe the scope of testing or integration. These dimensions provide complementary descriptions of function and validation. Field datasets support evaluation in realistic scenes, while whole-machine control trials connect automatic execution with measured responses and subsequent adjustment.

Sustainability-related conclusions were restricted to outcomes measured directly in the original publications. Reported reductions in water, fertilizer, pesticide, fuel, energy, labor, product loss, or residue-disposal demand were treated as operation-specific evidence. Broader system-level or life-cycle advantages were considered supported only when the comparison basis and system boundary—and, where applicable, the functional unit—were explicitly defined and the reported environmental, economic, or operational outcomes were consistent with that boundary. In the absence of such information, the relevant technology was described as having potential sustainability benefits or requiring further assessment rather than as providing a demonstrated whole-system advantage.

No statistical pooling or meta-analysis was conducted because the available studies differed substantially in experimental conditions, machinery, test scale, operating settings, and definitions of loss, damage, impurity content, throughput, and resource use. Accordingly, the quantitative values reported in this review should be interpreted as context-specific evidence. They support the identification of engineering relationships, performance ranges, and research priorities, providing a basis for condition-specific calibration of operating thresholds.

2.6. Evidence Distribution and Descriptive Appraisal

Table 1 summarizes the evidence categories and their distribution across production stages. The 183 publications comprised 5 Category A, 22 Category B, 54 Category C, 63 Category D, and 6 Category E publications, together with 33 secondary or background sources. Direct processing-tomato evidence (A and B) accounted for 27/183 publications (14.75%), or 27/150 non-secondary publications (18.00%). This distribution supports interpretation of crop-specific conclusions alongside conditionally transferable engineering evidence.

Table 1. Evidence categories and production-stage coverage of the cited literature.

Production Stage/Corpus	A	B	C	D	E	Secondary	Total
Overall corpus	5	22	54	63	6	33	183
Crop traits and machine adaptation	0	13	14	9	0	3	39
Seedbeds, tillage, mulch, and drip tape	1	4	1	8	0	2	16
Transplanting and establishment	1	1	10	18	0	3	33
Weeding, inputs, protection, and monitoring	2	14	21	10	1	12	60
Preharvest regulation	0	8	10	2	0	1	21
Cutting, pickup, and feeding	3	0	1	12	1	4	21
Separation, cleaning, and sorting	3	2	9	10	2	9	35
Collection, unloading, and transport	3	2	4	3	3	6	21
Residues, storage, and resource use	0	3	4	11	0	7	25
Intelligent control and cross-stage topics	0	2	26	27	2	19	76

Note: A–E are defined in Section 2.4; secondary sources are separate. The overall row count includes 183 distinct publications, each counted once. Stage rows overlap and sum to 347 assignments, not 347 independent publications or experiments. Each publication has one principal category; its stage-specific endpoints retain their measured scope.

Because publications could address several operations, production-stage coding yielded 347 assignments across ten stages (Table 1). Intelligent-control and cross-stage topics appeared in 76 publications; field management, crop protection, and monitoring in 60; and crop traits in 39. The stage-by-category matrix shows the evidence sources underlying this thematic coverage. For example, the 21 publications addressing cutting, pickup, and feeding included three Category A publications and 12 Category D publications; cross-crop measurements therefore contribute engineering approaches that can be calibrated through processing-tomato trials.

Table 2 summarizes principal technology groups, trial or sample origins, and selected validation contexts. Monitoring and state estimation accounted for 35 publications, harvesting and handling for 29, and nursery and transplanting for 30. Single-country origins were identified in 109 publications, multinational origins in one, and unspecified locations or no new measured-site evidence in 40; 33 secondary sources were listed separately. Validation contexts overlapped, including controlled or bench tests in 93 publications, crop-level open-field trials in 25, whole-machine field tests in 22, component field tests in 13, and commercial-operation records in four. Coverage across seasons, locations, and cultivars occurred in 28, ten, and 14 publications, respectively. These counts include tomatoes, other crops, and engineering systems. Functional scope, environmental coverage, and commercial deployment are interpreted separately, with the measured endpoints guiding transfer to processing-tomato operations.

Table 2. Principal technologies, trial or sample origins, and selected validation contexts.

Dimension	Category	n	Counting Basis
Technology	Crop traits and material mechanics	13	One principal group per publication.
Technology	Nursery and transplanting	30	One principal group per publication.
Technology	Tillage and covering operations	12	One principal group per publication.
Technology	Mechanical and precision weeding	6	One principal group per publication.
Technology	Water, nutrients, and agronomy	21	One principal group per publication.
Technology	Crop protection and health recognition	8	One principal group per publication.
Technology	Monitoring and state estimation	35	One principal group per publication.
Technology	Intelligent control and evaluation	9	One principal group per publication.
Technology	Harvesting, separation, sorting, and handling	29	One principal group per publication.
Technology	Residue processing and resource use	20	One principal group per publication.
Origin	China	54	Actual trial or sample origin.
Origin	United States	9	Actual trial or sample origin.
Origin	Other single-country origins	46	Grouped countries; see note.
Origin	Multinational origins	1	More than one country.
Origin	Unspecified/no new measured-site evidence	40	Not assigned from affiliations.
Origin	Secondary sources	33	No new study site assigned.
Validation	Controlled or bench test	93	Selected overlapping labels.
Validation	Crop-level open-field trial	25	Selected overlapping labels.
Validation	Component field test	13	Selected overlapping labels.
Validation	Whole-machine field test	22	Selected overlapping labels.
Validation	Commercial-operation records	4	Selected overlapping labels.
Validation	Multiple seasons or sample coverage	28	Selected overlapping labels.
Validation	Multiple sites or sample coverage	10	Selected overlapping labels.
Validation	Multiple cultivars or sample coverage	14	Selected overlapping labels.

Note: Technology and origin groups each sum to 183 publications. Validation rows are selected overlapping contexts and are neither exhaustive nor additive. They include tomatoes, other crops, and engineering systems. Multiple-season, site, or cultivar coverage does not, by itself, establish independent validation. The 46 other single-country origins comprise Hungary (5), Brazil (5), India (4), Japan (4), Spain (4), Russia (3), the Netherlands (3), Egypt (2), Saudi Arabia (2), Israel (1), Canada (1), Ghana (1), Indonesia (1), Colombia (1), Ethiopia (1), Bangladesh (1), Pakistan (1), Italy (1), Slovenia (1), France (1), Sweden (1), United Arab Emirates (1), South Korea (1).

The descriptive appraisal of the 150 non-secondary publications is summarized in Table 3. Information on validation environments and comparison designs was more frequently coded as R than was information on sampling, outcome completeness, and reproducibility. Seasons and locations remained unresolved in 11 publications. Validation design was R in 35, PR in 105, and NA in ten. The 35 R records comprised five internal resampling or prediction-sample assessments, ten crop-response tests across years or settings, and 20 additional device or model test conditions. This distinction supports condition-specific interpretation of reported performance and prioritization of further verification. The field states summarize documented methodological information; they are not combined into a quality score or interpreted as counts of independent external validations.

Table 3. Descriptive appraisal of methodological information in non-secondary publications.

Domain	Information Examined	R	PR	UV	NA
Q1 Experimental scale	Area, duration, mass or sample count, and statistical unit.	122	26	0	2
Q2 Validation environment	Laboratory, bench, greenhouse, field or commercial setting.	147	2	0	1
Q3 Seasons and locations	Trial years, seasons and actual sites or sample origins.	65	72	11	2
Q4 Sampling and replication	Sampling units and independent or technical replicates.	75	71	0	4
Q5 Comparison design	Controls, baselines, treatment design and uncertainty.	134	16	0	0
Q6 Validation design and independence	Data partitions, extra conditions and external tests.	35	105	0	10
Q7 Tested object	Crop, material, component, whole machine, model or surrogate.	150	0	0	0
Q8 Outcome definitions and completeness	Metric definitions, denominators, and measurement boundaries.	73	77	0	0
Q9 Processing-tomato specificity	Processing use and the measured crop or mechanical endpoint.	83	30	0	37
Q10 Reproducibility information	Operating settings, material state, procedures, and data partitions.	46	104	0	0

Note: Each row totals 150 non-secondary publications. R, reported; PR, partially reported; UV, unresolved; NA, not applicable. NR (confirmed not reported) was zero in every domain and is omitted from display. R denotes documented information, not a quality score or demonstrated independent validation. Q6 R comprises five internal resampling or prediction-sample assessments, ten crop-response tests across years or settings, and 20 additional device or model conditions.

3. Characteristics of Processing Tomato and Their Effects on Mechanized Production

3.1. Morphological Characteristics of Processing Tomato and Their Effects on Mechanized Operations

The suitability of processing tomato for mechanized production is governed first by plant morphology and stand architecture. Compared with fresh-market tomato, processing tomato is generally intended for large-scale open-field production and once-over harvesting; therefore, plant architecture affects not only yield formation but also machinery trafficability, plant cutting and guidance, continuous material feeding, and the stability of subsequent fruit–vine separation. Tomato shoot development involves successive sympodial units, and flowering regulation influences their reproductive development. Jiang et al. showed that MACROCALYX, FUL2, and MBP20 have overlapping functions in floral transition and reproductive meristem identity; loss of all three strongly delayed sympodial flowering and disrupted reproductive identity in the inflorescence meristem [7]. This provides a developmental basis for considering flowering and shoot architecture together. Building on these findings, joint evaluation of architecture, flowering, yield, and machine compatibility could help identify crop characteristics suited to processing-tomato harvesting. Figure 3 separately illustrates contrasting SELF PRUNING allelic effects on shoot architecture.

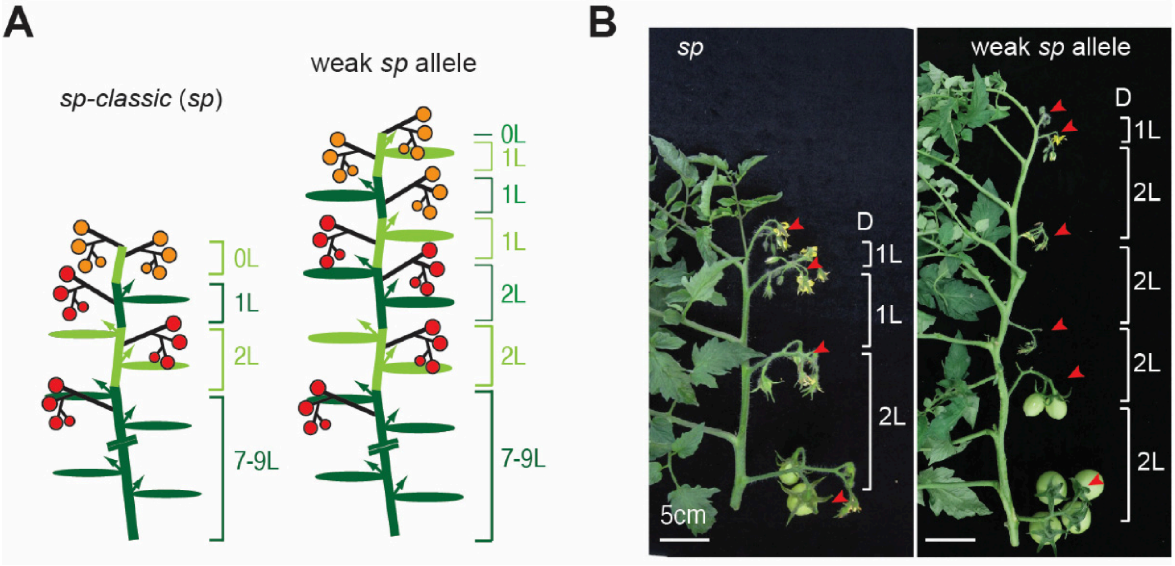


Figure 3. Contrasting sympodial shoot architecture of tomato plants with sp-classic and weak sp allelic effects [30]. (**A**) Diagrams illustrating the two plant architectures. Dark-green bars and ovals represent the primary shoot and its associated leaves; alternating light-green and dark-green bars and ovals indicate successive sympodial shoots. Arrows indicate axillary shoots, and black lines indicate inflorescences. Red and orange circles represent maturing fruits. (**B**) Representative main shoots of *sp-classic* and the hypothetical weak *sp* allele in three-month-old plants. Arrowheads indicate inflorescences; L denotes leaf. Scale bars, 5 cm [30].

Plant architecture sets the geometry of the material entering the harvester. Pinching research describes changes in processing-tomato growth and harvest timing [1], while flowering research explains developmental regulation [7]. These findings motivate joint assessment of plant architecture, feeding continuity, and blockage. Long, overlapping branches could form tangled bundles at cutting and pickup; uneven bundles could then overload conveyors or wrap around exposed rotating elements. The proposed feeding and entanglement mechanisms remain to be tested alongside the agronomic treatments. Header guides, guarded rotating parts, and matching conveyor speed to incoming biomass are candidate responses. Their performance should be assessed through feed-rate variability, blockage frequency, downtime, and recovered yield. Reducing canopy spread may ease feeding but sacrifice productive branches. Matched cultivar–header trials at the intended density and harvest moisture could support selection of suitable branch geometry for each production setting.

Canopy structure also affects the consistency of pickup and the fruit–vine stream. Gaps, lodging, and differences in canopy height or overlap are relevant crop states because they may produce intermittent pickup and uneven loading of the separator. Adjustable pickup height and guides, together with ground-speed adjustment when the incoming layer thickens, are plausible engineering responses. Operational stability is better characterized by variation in mass flow, missed plants, ground-fruit loss, and throughput than by visual canopy compactness alone. Lower travel speed can accommodate a variable canopy but reduces field capacity; more aggressive pickup may recover lodged material while increasing soil intake or fruit impacts. This pathway concerns open-field, once-over harvesting and requires measurement of canopy condition and header settings together. Research on reproductive development provides a biological basis for interpreting canopy architecture [7]; joint crop–machine trials could further clarify its relationship with pickup and harvest stability.

Flowering phenotype and stand maturity provide complementary information for harvest planning. Research on reproductive development explains flowering regulation in tomato [7], while evaluation of tomato materials addresses their suitability for mechanized cultivation [31]. These crop-level findings could inform the calibration of harvest criteria under local production conditions. A mixture of green, ripe, and overripe fruit presents competing demands: attached fruit must be separated, soft fruit protected, and unacceptable fruit rejected. Representative maturity sampling can inform harvest scheduling and separator intensity, while sorting settings should follow the processor's acceptance criteria. Relevant outcomes are recovered acceptable yield, fruit left on vines, ground loss, damage, and false rejection. Waiting for more red fruit may increase overripe damage or weather exposure; harvesting earlier may increase immature rejects. For once-over systems, combining ripe-fruit proportion and color with detachment-force and damage-resistance measurements would strengthen evaluation of this trade-off.

An operational cultivar screen should therefore pair canopy width, branch overlap, stand gaps, and maturity composition with machine measurements at the same location and date. Assessing blockage reduction alongside acceptable recovered yield and field capacity would capture its overall operational value. Architecture and maturity characterized in agronomic and developmental studies [1,7] provide inputs to this comparison; measuring feed stability, separation loss, and sorting rejects would connect those traits with operational outcomes.

Evidence from other crops can guide the design of such comparisons. Screening oilseed rape for low-loss mechanized harvesting illustrates a method for evaluating crop traits alongside harvest losses [32]. Adapting this approach to processing tomato could involve trials spanning cultivar, density, moisture, and header geometry to develop crop-specific criteria for vine length, feeding, and separation.

3.2. Physicomechanical Properties of Processing Tomato and Their Effects on Mechanized Operations

During harvesting, conveying, cleaning, collection, and transport, fruit encounter short impacts, sustained compression, and localized puncture loads. Fruit geometry and mass distribution help describe contact location and material-layer formation, while tissue-failure measurements add information on the response to loading. A crop–machine assessment should pair cultivar and maturity measurements with the actual contact surface, loading direction, rate, and duration. Quasi-static firmness, puncture resistance, and impact injury offer complementary endpoints for matching machine settings to the relevant loading mode [2–4,33].

Firmness becomes operationally relevant when related to a specified loading mode. Compression and puncture tests characterize the mechanical response of whole processing-tomato fruit [3], whereas tests on isolated cuticles examine the response of the protective outer tissue [34]. Chylińska et al. used Raman microspectroscopy to distinguish the distribution of cellulose and pectins in tomato cell walls [35]; these structural observations could be complemented by cell-elasticity and harvesting-damage measurements to connect tissue organization with handling response. Figure 4 illustrates complementary mechanical tests. A field comparison in industrial tomato also measured firmness after manual harvesting, mechanical harvesting, and bulk transport [36], linking crop resistance to actual handling stages rather than tissue structure alone. For relatively soft fruit, cushioning transfer points, limiting drop height, and avoiding deep or prolonged accumulation are candidate responses to impact and compression risks. Performance should include immediate rupture, internal or delayed injury, and retained processing quality. Gentler transfer can constrain throughput or require more space. Testing across relevant cultivars, maturity stages, temperatures, and loading directions would support condition-specific setting

selection. Reviews of robotic end effectors discuss designs for gentle fruit handling [37]. Controlled experiments with Momotaro tomatoes relate fruit dimensions and loading response to pneumatic flexible-finger design and single-fruit clamping [38]. These results provide a material–contact design approach that can be extended through continuous-flow tests with processing-tomato cultivars and bulk-transfer loads.

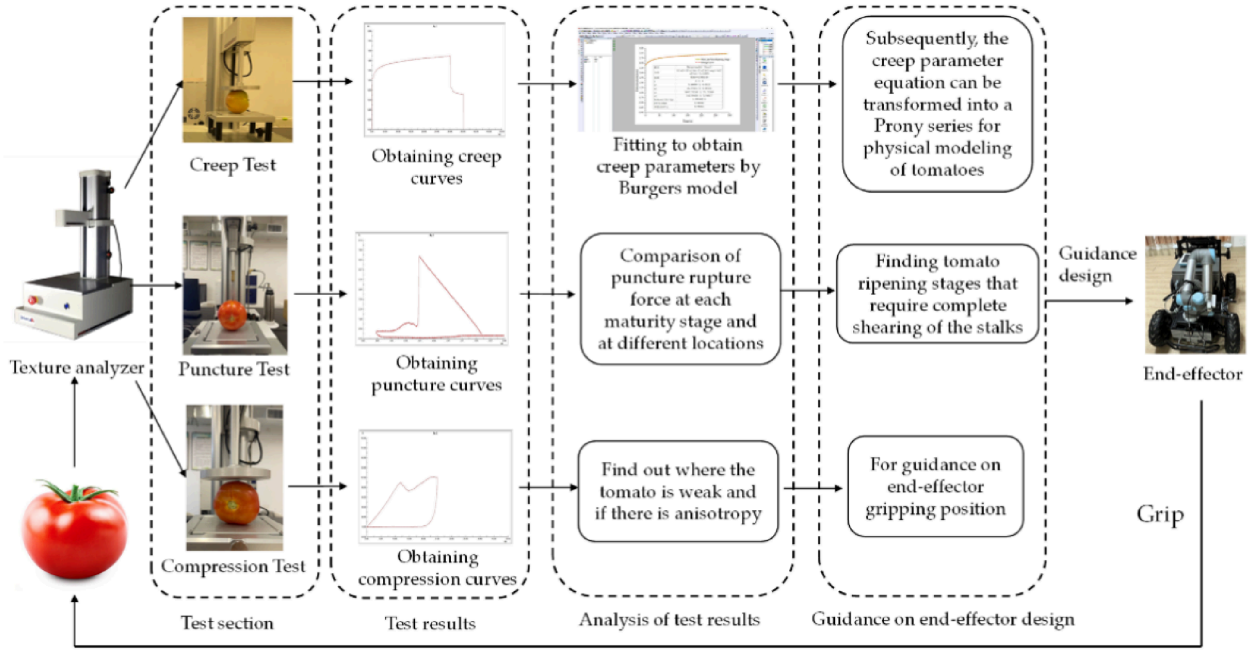


Figure 4. Framework of compression, puncture, and creep tests for tomato fruit mechanical characterization and equipment design [4].

Ripening changes tissue structure and load response. Posé et al. reviewed AFM evidence linking pectin disassembly with fruit softening across several fruits [39]; this synthesis provides a biological explanation that could inform whole-fruit loading tests and subsequent machine-setting calibration. In tomato tests by Zheng et al., mean exocarp puncture force declined from 9.224 ± 0.901 N at the green-ripening stage to 4.521 ± 0.654 N at the mid–late firm-ripening stage [4]. Puncture testing used a 2 mm probe at 1 mm/s to a 7 mm displacement, and creep tests applied 5 N for 300 s followed by 50 s unloading. Their creep fits had R^2 values above 0.99, with individual variation highlighting the value of firmness sampling alongside ripening stage. The laboratory values characterize the tested fruit and protocol and provide reference data for subsequent evaluation of harvester loading. Sampling firmness alongside maturity can inform cautious changes to transfer and separation settings; on-machine damage and recovery measurements would clarify the resulting performance.

Transient injury also has a time dimension: injured Deborah tomatoes lost firmness during ambient storage [5]. Direct processing-tomato evidence comes from impact monitoring of five commercial harvester models in Navarre, Spain [6]. Identifying model-specific critical points led to shaker-speed reductions or discharge cushioning and reduced drop height; some adjustments also included lower travel speed. Over four harvest periods, reported damaged-fruit percentages fell from 20–29% to below 10% [6]. This supports targeted adjustment of the handling chain. Follow-up trials separating the individual settings could clarify their respective contributions and help define condition-specific impact tolerances. Evaluating damage reduction alongside field capacity, product specification, and delayed quality change would support balanced operating decisions.

Cross-crop mechanical studies are most useful for informing test design. Experiments on wheat grains examined how moisture and loading rate affect mechanical strength [40]. Their test approach could inform tomato-specific evaluation of drop height, gripping force, and separator settings. For tomatoes, fruit size, orientation, maturity, and contact conditions should be recorded with each mechanical endpoint [3,4]. Imaging of tomato cell walls characterizes tissue organization [35], while the review of fruit softening relates pectin disassembly to changes in mechanical properties [39]. These findings could be considered alongside whole-fruit loading tests and commercial-machine trials.

Detachment characteristics define a different constraint from firmness. The distribution of fruit–pedicel detachment force, fruit mass, and the location of separation should be measured by cultivar and maturity before choosing vibration amplitude, frequency, and exposure time. Greater acceleration or longer exposure may detach more retained fruit, but can also increase impacts, damage, and vine fragments. Commercial-harvester evidence identifies the shaker and its exit as important impact locations and shows the value of model-specific adjustment [6]; further crop- and machine-specific trials could develop suitable excitation ranges. A candidate response is to adjust excitation and residence time to the incoming crop, then compare fruit remaining on vines, ground loss, damage, impurities, and throughput. The lowest excitation that meets acceptable recovery is a candidate operating objective. Combining static detachment-force measurements with dynamic trials in moving, tangled vine masses would support its calibration.

3.3. Agronomic Factors Affecting the Suitability of Processing Tomato for Mechanized Production

Equipment performance, cultivar, stand configuration, ripening progression, and water management jointly shape the plant and fruit conditions encountered during mechanized processing-tomato production. Cultivar choice is fundamental to mechanization suitability. A study by Vilas Boas et al. on four processing tomato cultivars showed that genotype significantly affected field fresh and dry fruit yield as well as quality traits including sugars, organic acids, and lycopene, and that its effect on purée viscosity was generally greater than that of maturity stage [41]. This indicates that evaluation of cultivars for mechanized production can complement yield and processing-quality assessment with plant-architecture uniformity, ripening synchronization, and consistency of fruit condition at harvest, so that material entering the harvester remains relatively uniform in maturity and quality.

Planting density, row geometry, and canopy expansion jointly shape the space available for mechanical passage. The 3.3 plants/m^2 used in one processing-tomato experiment [41] provide a stand-density reference that could be complemented by machine-clearance trials. Increasing density may increase biomass per unit area while reducing clearance as neighboring canopies overlap. Row and bed spacing should be matched to wheel tracks, implement width, steering error, and header capacity before establishment. Clear traffic lanes and appropriate guidance can reduce crop-contact risk, but wider lanes occupy productive land and lower density may reduce yield. Performance should be assessed through passable width at operation time, wheel or implement crop injury, field capacity, and acceptable recovered yield. Assessment of suitable spacing can combine density with machine dimensions, soil bearing condition, and canopy development to characterize trafficability under the intended conditions.

Maturity composition connects processing quality to the separation and handling trade-off described in Section 3.1. Harvest stage changed color and purée properties in processing tomato [41], and ripening changed puncture resistance in a separate tomato test [4]. These studies support recording maturity and resistance together; linking those observations with sorting trials could clarify their contribution to reducing sorting losses.

Representative preharvest green, ripe, and overripe fractions should be paired with acceptable recovery, rejects, and damage after harvest. Processor specifications and weather determine whether waiting for more ripe fruit outweighs the risk of handling softer fruit.

Water and nitrogen management influence growth, yield, and fruit condition, but their effects depend on timing and production setting. In two years of open-field processing-tomato trials in arid Egypt, Badr et al. compared sustained deficits with deficits applied at different stages [9]. Early-season water reduction followed by restoration did not significantly reduce yield in the tested treatment, whereas reduction after the onset of ripening reduced yield. Greenhouse experiments examine tomato responses to water and nitrogen supply [10], while processing-tomato trials compare genotype and irrigation effects on yield and quality [41]. Further trials could relate these responses to maturity synchronization. Irrigation scheduling and nitrogen supply should therefore be evaluated against repeated maturity samples, crop water status, acceptable yield, soluble solids, and measured machine loss or damage. Reducing irrigation may conserve water but can sacrifice yield; improved field access is a separate hypothesis that requires soil-bearing measurements. The cited experiments characterize yield and fruit-quality responses under their respective cultivars, soils, climates, and treatment stages. Further studies linking nitrogen management with maturity distribution and once-over harvesting performance could extend these agronomic findings to mechanized production.

Biotic disease and abiotic stress should be distinguished when assessing crop condition. Field and greenhouse work in California processing tomato showed that Fusarium wilt symptoms can occur in resistant cultivars and that disease-race differentiation depends on the phenotyping method [42]. This supports crop inspection and diagnosis and provides a basis for investigating how diagnosed crop conditions relate to feeding continuity and harvester blockage. Processing-tomato experiments examine crop responses to nitrogen supply and salinity [11], and mycorrhizal treatments have been evaluated under water scarcity [12]. Both sets of findings are interpreted within their respective stress conditions. For mechanization, patchy wilting, lodging, or deteriorated fruit should be recorded as crop states and paired with feeding interruptions, recovered yield, damage, and impurities. These disease studies motivate investigation of candidate responses such as segregating affected patches, adjusting travel and handling intensity, and adapting acceptance decisions. They may limit unsuitable deliveries while reducing field capacity or increasing rejects. Application can combine symptom observations with diagnostic confirmation, processor requirements, and matched machine measurements to guide suitable protection and handling decisions.

Sensing can support these decisions, but its validation scale matters. Tomato maturity-recognition research examines image-based classification of ripening stages [27,43,44]. Lawal developed a modified YOLOv3 detector for ripe and unripe tomatoes [45]. The latter used 125 images split into training and test sets, providing a basis for broader field sampling and evaluation of maturity-informed harvesting adjustment. Research on rice harvest-period monitoring offers a scheduling approach whose adaptation to tomato would require crop-specific evaluation [46]. For processing tomato, independent field testing could connect crop-state estimates with settings and subsequent acceptable recovery, damage, impurities, and throughput. Table 4 summarizes the proposed relationships and identifies where joint crop–machine measurements are still needed.

Table 4. Crop and agronomic conditions, machine responses, and evidence boundaries.

Crop/Agronomic Condition	Mechanically Relevant State	Engineering Response to Test	Performance at Risk	Evidence Boundary/Test Need
Architecture and canopy uniformity	Overlap, lodging; variable feed layer	Match pickup height, guides, and feed speed	Blockage, ground loss, throughput	Quantify geometry–feed relationships by cultivar and density
Maturity distribution	Maturity classes; measure attachment and damage resistance separately	Test separator settings and sorting acceptance against maturity mix	Detachment, damage, false rejection	Pair maturity sampling with recovery, rejects, and latent damage
Fruit firmness and rupture resistance	Tolerance to impact/compression	Test cushioning, drop height, and accumulation	Bruising, rupture, processing quality	Pair loading protocol with immediate and delayed damage
Stand, row, and ridge uniformity	Geometric alignment and trafficability	Match traffic lanes and guidance to machine and crop dimensions	Placement error, crop injury, missed plants	Measure canopy clearance and crop injury under field conditions
Fruit–pedicel attachment	Detachment-force distribution and fruit mass	Match excitation and residence time to crop state	Residual fruit, damage, loss, throughput	Combine static force with dynamic trials to calibrate frequency
Water, nitrogen, and harvest timing	Growth, fruit condition, maturity spread	Calibrate stage-specific management and scheduling	Water input, yield, quality, harvest losses	Pair maturity and machine outcomes to assess synchronization
Disease and abiotic stress	Patchy wilting, lodging, deteriorated fruit	Inspect, segregate patches, test handling adjustments	Acceptable recovery, impurities, damage, capacity	Diagnosis and matched crop–machine tests required

4. Mechanized Tillage and Planting Technologies for Processing Tomato

4.1. Commercial Plug-Seedling Production for Processing Tomato

Commercial plug-seedling production defines the material entering the transplanter. Light and carbon dioxide management affect tomato seedling growth and morphology [47], whereas mechanical conditioning provides a route to controlling excessive elongation [48]. For machine compatibility, nursery specifications should include tray-cell geometry, stem position, root-ball integrity, and moisture at pickup. Tomato end-effector experiments show that moisture, needle angle, and linkage design interact to affect successful extraction and delivery [49]. These properties help relate nursery quality to the operating requirements of planting machines. Comparative trials across processing-tomato cultivars, nursery practices, and machine configurations could support context-specific seedling specifications.

Seedling morphology should be evaluated against handling requirements rather than plant height alone. Garner and Björkman examined mechanical conditioning of tomato seedlings and subsequent field performance [48]. For transplanting, a compact canopy and a sufficiently robust stem are desirable because they leave clearance for the gripper and guide tube. This morphology–handling relationship provides an engineering rationale for testing compact seedlings. Extending the evaluation to machine miss rates, nursery labor, seedling damage, and post-transplant growth would help identify suitable conditioning practices.

Root-ball cohesion and release resistance jointly influence successful pickup. In an experimental pickup-and-transfer system, Periasamy et al. tested 25-day-old tomato seedlings in 98-cell coir-pith trays at a nominal frequency of 840 seedlings/h. Their abstract and conclusion report 93.45% successful picking and transfer at 18 ± 1% substrate moisture

content on a wet basis and an 8° needle angle with end-effector I [49]. This percentage describes successful handling; field placement and survival provide complementary later-stage outcomes. The abstract and conclusion values are used here, with clarification of the differing percentage in the results text useful for numerical comparison. Jin et al. linked tomato plug compression resistance and tray adhesion to gripper design in an indoor automatic transplanting device [50]. These settings are substrate- and device-specific. Studies of biochar amendments examine cucumber seedling growth and substrate responses [51,52]. Tomato-specific substrate and pickup trials could explore their relevance to mechanized nursery handling. In Shao et al.'s laboratory test of 38-day-old tomato seedlings in 105-cell trays, 210 seedlings were evaluated at each feeding frequency. Success meant extraction without damage, followed by discharge into a chain cup: 83.33%, 79.05%, and 73.33% at 6, 9, and 12 groups/min, respectively [53]. At 6 and 12 groups/min, feeding-stage missing rates were 4.29% and 8.57%, stuck rates 9.52% and 13.81%, and injury rates 2.86% and 4.29%. These categories characterize the feeding stage, with field missing-plant and establishment rates assessed subsequently. The results identify a frequency–delivery trade-off within one device; comparison with the pickup-and-transfer system evaluated by Periasamy et al. [49] would benefit from harmonized test conditions and field-capacity measurements.

Detection and handling address different failure modes. The computer-vision framework of Jin et al. uses seedling images to identify healthy potted seedlings [54]; its identification results offer a basis for subsequent handling and field-establishment evaluation. Jiang et al. measured extrusion and tray-adhesion forces during cucumber plug extraction and showed that substrate moisture, bulk density, and composition affect these forces [55]. This provides a method for matching gripping force to release resistance, which could inform tomato-specific calibration. The review by Han et al. identifies tray standardization, agronomic matching, and the speed–damage conflict as constraints on automatic pickup [56]. Vision-guided handling should therefore be evaluated jointly with empty-cell detection, extraction damage, and successful delivery, with the crop and test environment stated.

Nursery and pickup options are compared here using a common set of outcomes: effective work rate, planting quality, missing plants, uprightness, depth and spacing consistency, field adaptability, energy use, labor demand, economics, and validation maturity. Before field planting, extraction success, plug damage, and delivery continuity provide intermediate quality indicators; post-placement measurements of uprightness, depth, spacing, and establishment complete the planting assessment. Research on seedling extraction evaluates a robotic handling mechanism [57], while tomato experiments examine extraction and feeding performance [49,50,53]. Comparisons of these results need to account for tray specifications and test conditions. Additional energy, cost, and field measurements would extend these comparisons, while independent operating trials could establish the commercial readiness of laboratory prototypes and recognition-assisted systems.

4.2. Mechanized Tillage and Seedbed Preparation

Seedbed preparation links soil workability with opener penetration, seedling placement and subsequent traffic. Processing-tomato studies illustrate why reduced tillage options benefit from separate assessment [58,59]. In two non-irrigated Ontario sites in 1998–1999, Thomas et al. compared conventional, disk, zone and no-tillage with cultivar H9478 on sandy soils [58]. Conventional, disk and zone treatments had statistically comparable red- and green-fruit yields, whereas no-tillage reduced yields and delayed maturity. The zone treatment disturbed a 23-cm-wide, 15-cm-deep strip, and the transplanter used additional down-pressure and narrow packing wheels. Thus, localized disturbance and adapted placement equipment maintained crop performance under these conditions. Figure 5 illustrates the alignment requirements of flat and ridge layouts.

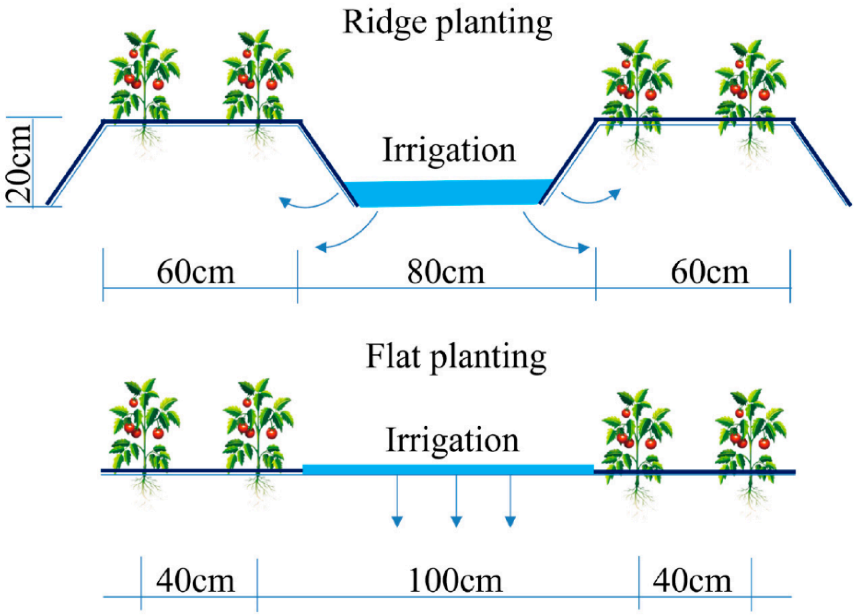


Figure 5. Schematic layout of flat and ridge planting systems for processing tomato under irrigation [60].

In a 12-year, furrow-irrigated cotton–tomato rotation at Five Points, California, conservation tillage preserved beds and confined tractor traffic to furrows [59]. For treatments without cover crops, the reported operation count fell from 16 to 10 trips per crop year. Annual resource requirements averaged over 2007–2011 were 24 versus 9 US gal/acre of diesel and 2.4 versus 1.4 machine-hours/acre for standard versus conservation tillage. The corresponding budgeted partial production costs before harvest were US$940 versus US$859/acre; land and irrigation-system costs were outside the accounting boundary. These results support reduced-pass management in that production system, with the economic advantage dependent on local prices and equipment utilization. However, higher cover-crop residues complicated transplant establishment, illustrating the trade-off between residue retention and reliable placement.

Other tomato systems provide complementary comparisons, including soil-property observations in no-till tomato production [61]. In irrigated organic tomato in Iowa, mean yields were 40 and 63 t/ha in 2006 and 2007, respectively, with no significant tillage-treatment differences, while no-tillage incurred additional cover-crop management costs [62]. A cross-crop organic-tillage meta-analysis further identifies soil and weed responses relevant to system selection [63]. Together with the Ontario and California results, these studies favor matching disturbance intensity to irrigation, residue cover and establishment conditions, while retaining the original crop and management context of each comparison.

Resource comparisons are most informative when they cover the complete preparation and weed-control sequence, including any corrective pass. Effective capacity, fuel, and labor per completed hectare can then be interpreted alongside bed uniformity and transplanting quality. A small battery-powered orchard tractor was evaluated through PTO loading and rotary-tillage tests [64]. Its operating-duration estimate was derived from short measurements of battery state-of-charge change, providing a load–energy assessment method. Matched measurements of soil condition, implement work, charging inputs, and acceptable bed preparation would extend this approach to comparisons of processing-tomato preparation systems.

After four years of a California cotton–tomato rotation, Veenstra et al. observed lower bulk density under conservation tillage, alongside surface salt accumulation and

soil-carbon loss where cover crops were absent [65]. Cover cropping increased carbon inputs and modified fertility responses. This supports condition-specific preparation rather than a universal minimum-disturbance prescription. For processing tomato, the selected sequence should maintain a plantable strip and aligned traffic lanes while accommodating salinity, residues, and film or tape placement. Mulch material choice adds installation and end-of-season considerations [13]. Crop-system trials and whole-machine establishment tests provide complementary evidence for this selection.

4.3. Mechanized Plastic-Mulch and Drip-Tape Laying Technologies

4.3.1. Mechanized Drip-Tape Laying

Drip-tape placement has been integrated with the Grimme GF-75/4 ridge former in potato systems [66,67]. Kizyaev et al. reported laboratory laying resistance of no more than 180 N at depths of 20–80 mm and subsequently mounted the device for field use [66]. Martynova and Balabanov reported a 3.0-m working width, a 0.9–1.4 m/s working-speed range and a 0.51–0.97 ha/h capacity range, using 16-mm tape with 300-mm emitter spacing [67]. The capacity range is retained as a reported equipment characteristic rather than normalized to a tomato field trial. These studies demonstrate a ridge-based integration route whose geometry and irrigation timing can be adapted to processing-tomato establishment.

The ridge-mounted design combines a depth-adjustable guide and opener with reel braking to limit overrun during stops [67] (Figure 6). These features support consistent placement and controlled tape payout during stop–start operation. Its reported traction increase of 6–8% was calculated, providing a design estimate for integration. A matched field comparison could determine how this extra loading interacts with soil resistance and operating interruptions.



Figure 6. Combined ridge-forming and drip-tape-laying equipment under field operation [67].

For processing tomatoes, tape position should match the bed, transplant row, and irrigation plan. The potato studies report installation feasibility and equipment characteristics [66,67]; depth variability, damaged tape length, reel-change time, and comparative fuel or labor requirements remain useful additions for tomato-specific assessment. Separate and integrated laying can therefore be compared on completed usable area, with any repair and loading time included. The tested potato settings provide a starting point for adaptation, with local soil and bed conditions guiding calibration.

4.3.2. Mechanized Plastic-Mulch Laying

Pathak et al. evaluated a 60-kg mulch-laying implement pulled by two operators on soil prepared with a rotavator and leveler [68]. The experiment used 1200-mm-wide film, thicknesses of 15, 20, and 25 µm, disc angles of 35°, 40°, and 45°, punch spacings of 250, 500, and 1000 mm, and speeds of 1.3, 1.5, and 1.7 km/h. These factorial trials compare operating settings within a manually assisted system; their results provide a useful small-scale reference for powered and integrated-machine assessment.

The speed-level means show effective capacity increasing from 0.11 to 0.19 ha/h and field efficiency from 72.04% to 89.51% between 1.3 and 1.7 km/h, while punching efficiency was 85.18%, 84.01% and 84.40% at the three speeds [68]. Film thickness introduced a separate trade-off: mean capacity increased from 0.142 to 0.149 ha/h between 15 and 25 µm, but punching efficiency decreased from 88.20% to 78.55%. Thus, the highest work rate and the most complete hole formation occurred under different settings. These factor-level means are not paired outcomes from a single optimal treatment. Punching efficiency denotes actual holes relative to expected holes, rather than film integrity or subsequent planting success.

The manually assisted configuration is relevant to small fields with available labor, whereas tractor integration adds traction, setup, and repair considerations. Although soil conditions form part of the study context, separate performance values by soil texture or moisture are not reported [68]. Such measurements, together with pulling effort, energy and cost, would clarify wider field suitability. The review of polyethylene and biodegradable mulches adds material-specific removal and degradation considerations [13]. Selection can therefore balance laying and punching performance against transplant alignment, installation labor and end-of-season management.

4.3.3. Combined Drip-Tape and Plastic-Mulch Laying

Combining ridge formation, tape laying and mulching can align operations on a common frame, as illustrated by ridge–tape integration in potato [67]. Bed formation itself has been evaluated more quantitatively. Sawant et al. tested a variable-width former in a soil bin at 11%, 13%, and 15% soil moisture on a wet basis, with widths of 0.7, 0.8, and 1.0 m and speeds of 0.42, 0.56, and 0.69 m/s [69]. Field evaluation used clayey soil, approximately 13.25% moisture, a 1.0-m working-width setting, and a 55-hp tractor after plowing, cultivation, and rotavation. At 0.56 m/s, measured draft was 4349 N and fuel use was 4.5 L/h. These are bed-former results, providing a component benchmark for subsequent integration.

At 1.25 m/s, the same bed former used 5.7 L/h and formed a bed 180 mm high, with 0.90-m top and 1.1-m bottom widths [69]. These field dimensions illustrate why speed comparisons also need a common finished-bed specification. Hourly fuel figures characterize the tested operation; energy per completed hectare additionally depends on effective width and elapsed-time capacity.

The RBF neural network–PSO approach predicted specific draft from the soil-bin data, with a 7.21% difference between the selected prediction and the field measurement [69]. This supports condition-specific parameter estimation. Adding film, tape, and planting units introduces loading and alignment interactions that can be assessed through coupled trials. Across additional soils and operating ranges, recorded bed geometry, tape offset, and film damage would connect prediction performance with usable establishment output.

Separate operations retain flexibility to change bed geometry or repair individual units; integration reduces separately scheduled passes but couples adjustment and down-time. A common finished-bed specification and completed-area boundary would support comparison of fuel, labor, ownership cost, and interruption time. Mulch studies inform

installation and end-of-season handling [13], while the semi-automatic transplanter study supplies separate seedling-placement evidence [70]. Dedicated film- and tape-recovery measurements would complete the assessment of compatibility with harvesting and residue handling. The preferred configuration consequently depends on field size, soil workability, turning space, and equipment utilization.

4.4. Mechanical Transplanting of Processing Tomato

Semiautomatic field planting and automatic laboratory pickup represent different levels of validation. Javidan et al. evaluated a manually fed, single-row conical-cup tomato transplanter on plowed and leveled soil using four-leaf seedlings, a target within-row spacing of 35 cm, forward speeds of 1, 2 and 3 km/h, and depth settings of 5 and 10 cm [70]. The authors selected 2 km/h and 5 cm as the preferred combination. Increasing speed significantly affected deployment angle and physical damage, while the depth setting affected deployment angle; spacing differences were not significant. The source study reports mean angles from vertical of 1.83°, 2.75°, and 5.58° across the three speeds, providing field-placement evidence for the speed–quality trade-off. These angles describe mean placement orientation; reporting the share of plants within a stated uprightness tolerance would add a complementary quality measure. Clarification of replication and capacity definitions would also strengthen comparison of effective field rates. Manual feeding remains part of the operating system. A matched comparison of crew-hours, energy, and cost with automatic pickup experiments [49,53] could extend the field study's locally tested placement settings into an assessment of automation options.

Dibble and furrow systems respond to different soil and mulch conditions. Research on pneumatic dibbling examines hole formation in plastic mulch [71], while tests of a powered transplanter compare dibbler and furrow arrangements [72]. Non-circular gear generation with addendum modification was evaluated by gear-profile measurements and a six-row rice-transplanter field test [73]. With 38-day-old Nennong No.6 seedlings, 150-mm mud depth, and 200-mm plant spacing, reported missing rates rose from 3.3% to 5.5% as planting frequency increased from 140 to 180 plants/min. This manufacturing-to-operation comparison supports trajectory design; tomato-specific tests under dry-bed and mulch conditions can establish suitable penetration, release, and soil-closure settings. Mechanism selection should therefore test hole or furrow integrity, soil closure, uprightness, and depth consistency under the intended bed, residue, and moisture conditions. Comparable energy and cost measurements within a common operating boundary would support selection among these designs.

Automatic feeding removes repeated hand placement but introduces a coupled extraction–transfer–planting sequence. Laboratory experiments with tomato seedlings quantify extraction and delivery [49,53]. Field-planting trials could connect these handling results with placement and establishment outcomes. For air-jet-assisted pickup, Han et al. evaluated a laboratory prototype using 128-cell trays with cucumber, pepper, and cauliflower seedlings aged 21, 42, and 30 days, respectively [74]. The orthogonal tests varied root-lump moisture over 50–70%, whole-row versus individual ejection, protective pads, and picking settings of 120 and 140 plants/min. In the reported optimum-level verification, pickup success reached 90.75% for cucumber, 94.49% for pepper, and 92.61% for cauliflower. The percentages reported in the source study are retained; clarification of their relationship with the accompanying failure counts would facilitate consistent numerical comparison. Their success definition accounts for failures and damage during loosening, extraction, transfer, and discharge. Differences in these criteria limit direct comparison with the tomato feeding experiment by Shao et al. [53]. These cross-crop component results offer a basis for processing-tomato field trials measuring missing-plant

rates, effective area capacity, and compressor energy per acceptable planted seedling. Matching moisture and air supply to tomato root-ball and tray conditions would support crop-specific adaptation. Automatic-transplanting literature includes reviews [14,75] and prototypes addressing tray feeding, pickup, transfer, and metered placement under different crop and validation conditions [15,76–82]. A three-arm mechanism was tested with 30-day-old Nanjing 9108 rice seedlings in a 14 × 29-cell soft tray while the transplanter chassis remained stationary [78]. Its pickup endpoints complement whole-row air-assisted vegetable-seedling handling [79]. In a separate punching-and-transplanting mechanism, tests with 65-day-old pepper seedlings achieved 92.4% pickup success; the test sequence did not include conventional soil covering and pressing [80]. For sweetpotato seedlings carried on a pretreatment belt, a motor-coordination bench test at a target spacing of 25 cm reported spacing coefficients of variation of 7.42%, 9.34% and 13.29% at 0.2, 0.3 and 0.4 m/s, respectively [81]. These findings distinguish extraction reliability from speed-dependent placement uniformity. Flexible pickup-gripper research offers another contact-design approach [82]; common tomato-tray conditions and subsequent field-establishment measurements would support comparisons across mechanisms. Studies of rice seedling throwing describe a handling mechanism [83], and strawberry seedling recognition examines orientation detection [84]. These approaches could be explored in tomato whole-machine trials. Figure 7 illustrates programmed seedling pickup and photoelectric detection linked to vehicle movement [85]. The source prototype contributes chili plug-seedling evidence on programmed sequencing and photoelectric position feedback. Building on this approach, camera-based localization and feedback from measured planting quality could be evaluated in processing-tomato systems.

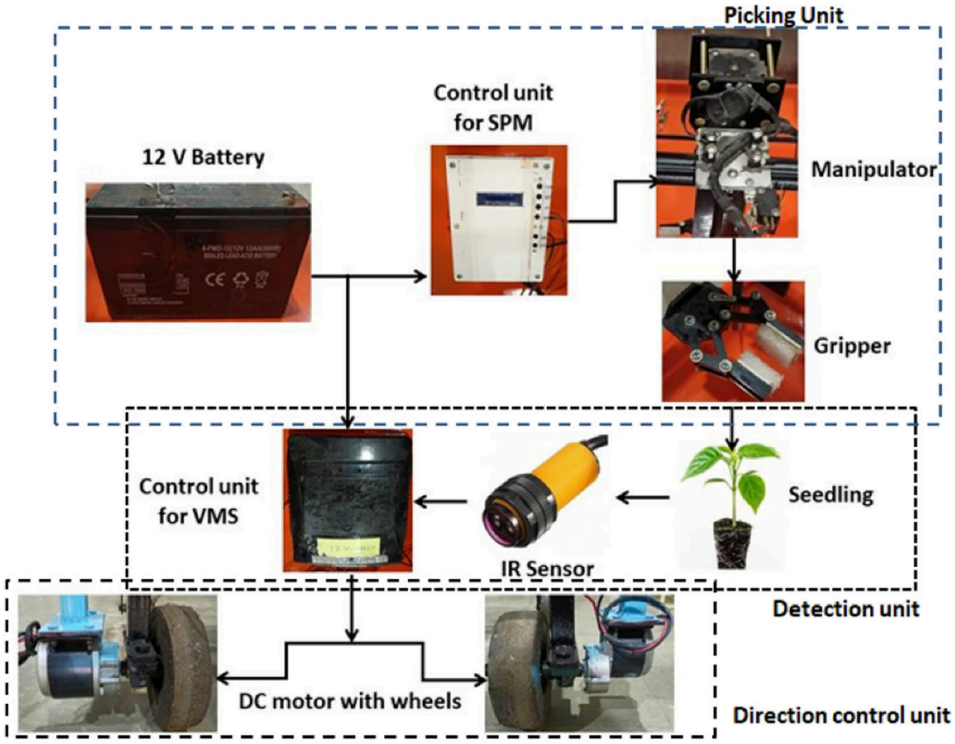


Figure 7. Picking, seedling detection, and vehicle direction-control units of a programmed robotic transplanter evaluated with chili plug seedlings [85]. This chili-seedling example contributes cross-crop guidance and sequencing insights for further processing-tomato development [85].

The available evidence supports selection according to operating conditions and validation scope. Semi-automatic transplanting has been evaluated for tomato field placement but retains manual feeding [70]. Automatic pickup systems contribute tomato extraction

and delivery results for subsequent field-establishment trials [49,53]. Air-assisted pickup offers high-rate laboratory handling results in other vegetable crops, providing a basis for processing-tomato field-performance and energy-use evaluation [74]. The selected pickup studies [49,53,74] provide handling-performance data; additional measurements of total cost per hectare, sustained field labor demand, and energy per acceptable planted seedling would extend economic and resource-use comparisons. Image-based broccoli seedling detection provides a sensing approach [86], while reviews of automatic seedling pickup summarize integration requirements [56,75]. Controlled comparative trials could relate these approaches to planting performance. For consistent future comparisons, this review distinguishes stage-specific metrics. Field missing-plant rate is the proportion of intended planting positions left empty immediately after placement, before manual correction; feeding misses are counted separately against seedlings presented to the feeder. Uprightness is the stem angle from vertical after soil closure, with the tolerance and the denominator of assessed placed plants stated. Depth consistency is assessed from measured placement depths relative to the local soil surface and target, complementing the machine's nominal depth setting. Spacing consistency concerns successive plant centers in the same row, with gaps caused by misses identified separately; reporting sample size alongside means, dispersion, or tolerance-based pass rates supports interpretation. Establishment or survival complements pickup success through a later assessment of live plants among planted seedlings at a stated interval. Effective work rate counts completed acceptable placements or area over elapsed operating time, including tray replacement, turns, and stoppages. Using the same boundary for energy, labor, and cost would support consistent comparisons. These definitions connect handling, placement, and establishment outcomes and provide a basis for further evaluation of tolerances, field survival, and commercial readiness.

5. Mechanized Field-Management Technologies for Processing Tomato

5.1. Intercultivation and Mechanical Weeding

Early after transplanting, weeds compete with processing tomato, while exposed soil leaves space for inter-row cultivation. As the canopy spreads, access narrows and the risk of root or shoot injury increases. Inter-row tools disturb soil between rows; intra-row tools must work close to plants and maintain a crop-protection zone [87,88]. Machine-vision recognition of crop-free ridge centerlines provides a guidance method for exposed-bed conditions [89]. A review of the physical cutting of weeds relates blade geometry, cutting speed, and plant-material state to cutting force and energy [90]. Combining these guidance and cutting-mechanics contributions with tomato-row trials would help match tool position and cutting intensity to crop clearance. The practical comparison is weed suppression and crop injury at a stated travel speed, working depth, soil condition, and growth stage. Increasing the disturbed area may improve weed removal while reducing selectivity; therefore, the operation should precede canopy closure where access and soil workability permit.

Cirujeda et al. compared physical weed-control methods in processing tomato in northeastern Spain over 2005–2011 [87]. In the initial 2005–2008 trials, flamer, torsion weeder, finger weeder, flex-tine harrow, and brush hoe were tested alone or in combination. Crusty soil made several treatments irregular and increased the need for additional tools or repeat passes. The selected brush hoe, working at about 5 cm depth, was then compared with polyethylene, biodegradable plastic, and paper mulches in 2009–2011. Across the seven-year study, weed biomass reduction exceeded 80% in six years, and brushed plots produced yields similar to those under the compared mulches. This weed-biomass endpoint characterizes control under the stated soil and management conditions, complementing weed-level detection and removal measurements in future comparisons. The comparison

supports brush hoeing as a locally tested option while retaining the trade-off between soil disturbance, repeat passes, and crop protection. Energy, labor, cost, and trials on additional soils would complement the reported yield and weed-biomass results and support wider operational comparisons.

Vision-guided weeding separates target recognition from tool intervention. Figure 8 illustrates the distinction between inter-row and intra-row tool operation [88].The tomato field-image example in Figure 9 concerns crop–weed discrimination [91]. As a cross-crop sensing example, Milioto et al. used RGB–near-infrared images from sugar beet fields, with 867 images in dataset A and 1102 in dataset B acquired two weeks later [92]. Dataset A was divided into 70% training, 15% validation, and 15% testing. Classification accuracy fell from 97.3% on its held-out test set to 89.2% on the later-stage test set; weed precision and recall were reported separately. These values describe image classification; subsequent intervention trials could connect recognition performance with physical weed removal and tomato protection.

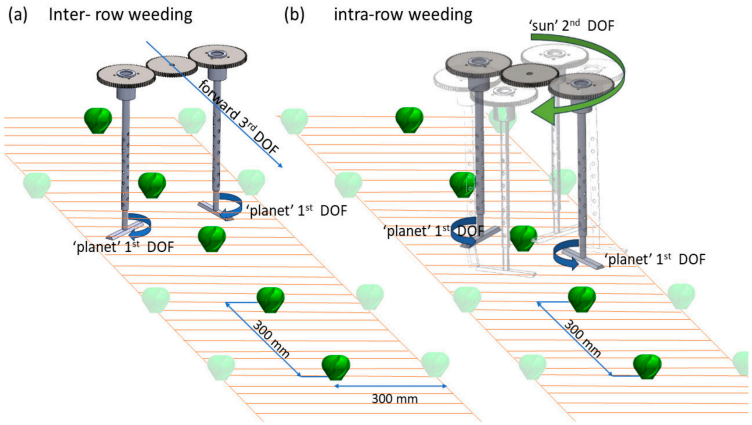


Figure 8. Scheme of machine working principle: (**a**) inter-row weeding; (**b**) intra-row weeding [88].



Figure 9. Machine-vision detection of tomato plants and weeds under real field conditions [91].

Mechanical intervention adds an operational dimension to classification, including image-to-tool displacement, timing delay, depth variation, and crop contact. Tests of small-scale vegetable equipment examine inter-row and intra-row tool operation [88], while a visual SLAM–inertial system couples pose estimation with steering in combine-harvester field tests [93], and path-tracking research contributes complementary guidance methods [94]. Joint measurement of tool-operation and navigation endpoints would support a common assessment of tomato-weeding efficiency. An engineering response is to match the safety clearance and tool timing to plant spacing and travel speed, then measure

missed weeds, crop injury, and effective field capacity. Narrower clearance or stronger disturbance can improve removal while increasing injury risk. Feedback on tool position or intervention outcome could extend camera-guided actuation toward closed-loop weeding.

A review of weed recognition in grain-production systems summarizes image-based methods [20], and sugar-beet experiments evaluate crop–weed classification across growth stages [92]. Processing-tomato trials could connect these recognition approaches with actuator performance. Tomato-specific testing could connect localization error and latency with the crop-protection zone, using classification precision/recall alongside weed-control efficacy, crop injury, yield, and labor to evaluate transfer. Milioto et al. reported lower classification accuracy when a sugar-beet crop–weed classifier was evaluated at a later growth stage [92], highlighting the importance of validation across crop developmental stages. Season-long processing-tomato trials linking classification with weed-control efficacy, crop safety, and yield would help translate these recognition findings into field-management practice.

5.2. Integrated Water and Fertilizer Management

Water and nutrient supply affect crop growth, but fertilizer-source suitability and delivery-system performance are distinct questions. Digestate trials in greenhouse and field tomato compare nutrient sources and crop response [95]. More directly, Barzee et al. tested processed digestates in subsurface drip-fertigated processing tomato in California in 2016, with four replicate plots per treatment and mechanical harvest [96]. The dairy-manure permeate and food-waste concentrate could be delivered after suitable processing; the dairy-manure concentrate treatment was abandoned after its first application because of particle agglomeration. This directly links amendment properties to a machinery constraint. These findings show how nutrient recycling can be supported by suitable filtration, handling, and emitter delivery; joint resource and delivery measurements could clarify its precision and environmental outcomes.

Water supply, soil condition, and crop objectives provide the basis for calibrating nitrogen recommendations. In the processing-tomato digestate trial, the mineral-N, food-waste concentrate, and dairy-manure permeate treatments delivered approximately 202 kg N ha^{-1} through fertigation, in addition to the common preplant treatment [96]. This nutrient-source comparison provides a basis for further nitrogen-rate and nitrate-leaching assessments. Experiments under greenhouse water–nitrogen treatments [10] and saline-soil processing-tomato conditions [11] characterize crop responses in different production settings. These responses could inform locally calibrated nitrogen recommendations. For machinery, nonuniform delivery can create spatially uneven growth; its consequences for feeding load and maturity distribution remain engineering questions unless those endpoints are measured.

Emitter configuration and fertigation frequency offer complementary ways to manage root-zone supply. The cherry-tomato studies [97,98] concern emitter density and root-zone responses, whereas Feng et al. investigated fertigation frequency under alternate partial root-zone drip irrigation [99]. These interventions change different aspects of water and nutrient distribution. Their treatment-specific findings can inform locally calibrated schedules when considered alongside irrigation amount, fertilizer dose, soil texture, and root-zone sampling depth. Increasing frequency may reduce dose per event but increases valve cycles and management demands; emitter layout must also be compatible with bed geometry and field establishment. Pumping energy and maintenance require separate measurements.

Water–nutrient combinations can favor different endpoints. Wang and Xing studied solar-greenhouse tomato over three consecutive growing seasons using irrigation levels of 100%, 75%, and 50% of reference evapotranspiration (ET0) and three combined N–P–K

fertilizer levels [100]. The highest reported yield was 95.8 t ha^{-1} at the highest water and fertilizer combination. In contrast, moderate irrigation with high fertilizer ranked first in both fruit-quality analysis and combined yield, quality, water-use efficiency, and fertilizer partial factor productivity analyses. Thus, the preferred combination depends on the chosen objective, with fertilizer responses interpreted for the combined nutrient treatment. A field study in Ethiopia compares tomato responses to irrigation and nitrogen treatments [101], while research on paddy evapotranspiration offers water-accounting methods for crop-specific adaptation [102].

Clearly defined denominators and boundaries support interpretation of resource-saving outcomes. Water-use efficiency based on crop evapotranspiration differs from irrigation water-use efficiency based on applied irrigation; fertilizer partial factor productivity describes output per fertilizer input, with nitrogen recovery and leaching providing complementary nutrient-fate indicators. The definitions and controls of nutrient-source trials [95,96] and rate-combination experiments [100,101] provide the basis for consistent comparison. Precision-irrigation and irrigation-practice studies contribute sensing, management, and delivery approaches [103–106]. A review of emerging sprinkler technologies adds low-pressure application, scheduling, and controller-design concepts [107]. These complementary approaches can inform integrated processing-tomato trials that pair crop response with measured delivery and resource inputs. More uniform supply may improve agronomic consistency, while extra sensing, pumping, filtration, and maintenance can offset resource savings; measuring these costs alongside yield would clarify the net resource outcome.

The demonstrated function determines the role of each element in the control chain. Moisture, salinity, flow, or crop observations are information acquisition; interpreting stress is state identification; calculating a dose is decision support; switching a pump or valve is automatic execution. In a closed loop, measurement of the resulting state feeds into adjustment of the subsequent action. The experiments discussed above establish treatment responses and delivery feasibility, providing a foundation for adaptive fertigation trials in open-field processing tomato. Crop responses may motivate downstream maturity and machine-load monitoring, but a controller benefit requires comparison with a stated baseline and measured water, nutrient, yield, quality, and energy outcomes.

5.3. Mechanized Crop Protection

Mechanized spraying should be assessed through deposition on the target canopy, off-target loss, and biological efficacy, rather than travel speed alone. Braekman et al. compared application techniques in greenhouse strawberries and tomatoes [108]; the greenhouse setting and nozzle arrangement constrain transfer to low, spreading processing-tomato canopies. Deposition improvements provide a basis for complementary assessment of disease control, pesticide use, and operator exposure. The crop–machine issue is whether the nozzle configuration reaches the relevant canopy layers while maintaining an acceptable application rate and loss. Ground systems permit close nozzle positioning but require field access; canopy closure, terrain, and traffic restrictions may limit their operating window.

Li et al. compared an inter-row lifting spray with a fixed-boom mode on mature tomatoes in a Chinese solar greenhouse [109]. At 0.3 MPa, with lifting speed 0.2 m s^{-1} and fixed-boom travel speed 0.3 m s^{-1}, mean deposition on leaf upper/lower surfaces was 1.77/0.817 µL cm^{-2} for lifting spray and 1.12/0.086 µL cm^{-2} for the fixed boom. The reported mean deposition coefficients of variation were 7.3%/19.53% versus 33.2%/74.7%, respectively. The two motion speeds describe different actions, providing a basis for future comparisons using a common field-capacity definition. Height-sensor-linked lifting demonstrated automatic positioning; incorporating crop-health assessment and treatment-

response feedback could extend this approach toward adaptive disease control. Adaptation to once-over-harvest field stands would benefit from joint evaluation of canopy penetration, exposure time, and mechanical complexity.

Tests of a multi-nozzle vertical-boom electrostatic sprayer in tomato examine how target distance, pressure, and voltage affect deposition [110]; Figures 10 and 11 illustrate the sampling arrangement and operating configuration. This work contributes application-physics evidence that complements pathogen-identification studies. Charging and nozzle positioning are candidate responses to limited leaf-underside access, with coverage, deposited dose, and biological efficacy providing complementary assessment measures. Electrical hardware adds power, maintenance, and safety requirements. Building on these greenhouse deposition results, matched field trials with hydraulic and air-assisted spraying could evaluate pesticide use, canopy deposition, and biological efficacy.



Figure 10. The arrangement of water-sensitive paper for tomato crop sampling [110]. Orange dashed lines mark the upper, middle, and lower sampling levels (Top, Middle, and Bottom). Black dimension arrows indicate the vertical heights and distances shown; the 55° markings denote the half-angle of the nozzle spray pattern (110° in total). The yellow arrow links a marked sampling point in the canopy photograph to the close-up view of water-sensitive paper attached to a leaf [110].



Figure 11. Inter-row operation of a multi-nozzle vertical-boom electrostatic sprayer in a tomato canopy [110].

UAV application reduces the need for ground access but changes the deposition problem. Çömlek et al. tested four hydraulic nozzle types at 40 L ha^{-1} and 2.4 bar using water-sensitive papers on horizontal and vertical platforms, rather than tomato canopies [111]. The highest mean horizontal coverage was 6.40% with an LU nozzle; the highest vertical coverage was 1.89% with an IDK nozzle. The preferred nozzle therefore depended on target orientation. These platform-coverage values provide a starting point for tomato leaf-deposition and pest-control trials. UAV and ground systems should be compared under matched dose and canopy conditions before ranking biological effect, drift, effective capacity, energy, labor, or cost; additional measurements would broaden assessment of these outcomes.

The use of plant-health information in crop protection involves distinct stages of detection, diagnosis, and intervention planning. Symptom detection identifies a visible or sensor-derived anomaly; disease diagnosis identifies its cause using suitable corroboration; a protection decision additionally considers severity, pest population or disease risk, intervention threshold, weather, and permissible treatment. Jelali's tomato disease/pest review synthesizes leaf-image recognition approaches and highlights the value of field testing and diagnostic corroboration where symptoms are visually similar [112]. Research on target sensing for orchard spraying offers approaches developed for orchard canopies and their application conditions [113]. Health-related changes in architecture, tissue condition or firmness, and maturity distribution offer pathways for investigating feeding, damage, and loss. Pairing image-derived health observations with machine trials could clarify these relationships.

Sensor-linked spraying encompasses target acquisition, state identification, application recommendations, and automatic output adjustment; the demonstrated functions determine the scope of each system. Spray-deposition studies characterize application performance under greenhouse or platform-test conditions [108–111]. Diagnostic confirmation and assessment of biological efficacy could extend these findings to crop-protection outcomes. Closed-loop crop protection requires measured feedback, such as achieved application output or crop/pest response, to alter subsequent operation. Trials of digestate delivery through drip fertigation examine nutrient supply [96], while the tomato disease and pest review discusses image-based recognition [112]. These contributions address different aspects of crop-health management. Linking health to harvestability requires joint observations of crop structure, fruit mechanics, maturity composition, and machine outcomes; such linked trials could extend the reviewed spraying results to harvestability assessment.

5.4. Crop Monitoring and Field Information Acquisition

Crop monitoring should specify both the sensor and the estimated endpoint. Diffraction imaging counts gray-mold spores from greenhouse-grown Zhefen 202 tomatoes, with microscopic counts providing the reference [114]. Grain-field boundary measurement illustrates spatial mapping [115], whereas electrical impedance spectroscopy characterizes maturity-related changes in greenhouse-grown Hybrid 908 tomato fruit [116]. These methods address pathogen abundance, spatial structure, and fruit state, respectively. Connecting these observations to crop-specific risk and maturity models can support inspection, treatment assessment, and harvest-readiness evaluation. For processing tomato, useful observations include canopy extent, gaps, temperature, yield potential, maturity composition, and signs of poor health. Converting these observations into a state estimate requires a suitable ground reference, acquisition conditions, and explicit uncertainty; linking the resulting maps to agronomic and machine-response models would support treatment and setting decisions.

Hyperspectral sensing estimates water status in wheat [117], while greenhouse-tomato leaf spectroscopy examines leaf sugar, nitrogen, and their ratio [118]. These approaches operate at different crop and sampling scales. Together, these studies contribute sensing approaches that could inform development of an integrated processing-tomato water–nutrient controller. Proximal optical sensing in sweet pepper examines the sensitivity of nitrogen measurements to acquisition conditions [16]. Tomato-specific calibration could support its adaptation to the proposed monitoring system. Documenting units, spatial scale, reference measurements, and prediction error would support conversion of crop estimates into calibrated irrigation or fertilizer recommendations. Independent observations after execution would connect actuator commands with measured changes in crop condition and help assess intervention outcomes.

UAV yield studies offer direct tomato observations but differ in validation scope [119,120]. Tatsumi et al. established 210 unstaked processing-tomato plants of cultivar Natsunoshun at one Japanese site in 2020, collecting RGB and multispectral imagery on ten dates [120]. The established field population and modeling observations describe different sampling stages: the paper reports 120 training observations as 80% of the modeling data, with the remaining 20% used for evaluation. The reported split therefore describes the modeling observations within the established field population. Random forest, ridge regression, and support vector models were evaluated with R2 and relative RMSE; models using selected first- and second-order features reported relative RMSE of 8.8–28.1% across individual-plant shoot mass, fruit weight, and fruit number predictions. These within-study plant-level estimates provide a basis for independent multi-site and multi-year validation at commercial whole-field scale. More flights and features increase collection and processing burdens; testing should determine whether the predictive gain changes harvest planning or field operations, with resource-use measurements complementing prediction-error assessment.

Ground sensing can resolve individual plants more closely than aerial imagery, but incurs access and occlusion constraints. Ambrus et al. examined field-grown tomato yield estimation using RGB observations and point-cloud segmentation with three-dimensional shaping [121]. This provides field-sensing evidence that could support subsequent trials of estimate-informed machine adjustment. Three-dimensional reconstruction and repeated viewpoints address spatial coverage; their use for unique-fruit counting additionally requires registration and checks for repeated observations. RGB-D-based pose estimation locates tomato peduncle nodes for greenhouse bunch harvesting [8]. These methods retain a role in geometry acquisition and target localization, with crop arrangement, reference measurements, and validation scale guiding their operational application. Ground-robot trafficability and processing time need to be evaluated before the resulting plant or fruit estimates can support commercial processing-tomato harvest scheduling.

Fruit detection, tracking across observations, unique counting, maturity classification, and internal-quality estimation require separate ground truths. Afonso et al. trained greenhouse Mask R-CNN detectors on 83 images and evaluated 40 images, with 1074 and 538 annotated fruits, respectively [122]. Red and green classes were imbalanced; depth-based background rejection improved precision but reduced recall. Their per-image detection results provide a basis for plot-level yield and multi-view counting studies. Consistent fruit identities across frames and reconciliation of repeated views could connect image detection with unique counting. Li et al.'s greenhouse maturity detector [19] offers complementary maturity information for further field-wide harvest-scheduling trials. Portable near-infrared spectroscopy offers another approach to fruit-quality analysis under field conditions [123]. Xiang et al. tested laboratory hyperspectral estimation on 200 ripe Zheyingfen-1 cherry tomatoes from 50 plants, split into 140 training, 20 validation, and 40 test fruits [124]. SSC prediction reached R2 = 0.901, while firmness prediction reached

about 0.53, indicating different calibration performance for the two traits. These single-cultivar, controlled-imaging results offer a starting point for processing-tomato firmness calibration, impact-damage assessment, and on-machine sorting trials. Grape and apple vision studies [125,126] contribute further methods whose adaptation could be explored using independent tomato datasets.

Validation criteria depend on the sensing or prediction task. Yield regressions require absolute and relative prediction errors; detectors require class-specific precision, recall, and the overlap threshold; tracking requires identity consistency across frames; counting requires error in unique fruit totals; quality models require calibration against measured SSC or firmness. Splits should separate repeated observations of the same fruit, plant, plot, or video sequence, with augmentation confined to training partitions to preserve test independence. The cited tomato examples [119,120,122,124] provide complementary task-level evidence, with independent trials across processing cultivars, sites, and years offering a valuable extension. Lighting, canopy occlusion, growth stage, and sensor changes can shift the input distribution. Implementing actuation translates monitoring recommendations into automatic execution, while measured-response updates add closed-loop control to the decision process.

5.5. Preharvest Field Regulation

Preharvest irrigation should balance processing quality, acceptable yield, and crop and soil condition for once-over harvest. Studies have evaluated final-irrigation timing [127], deficits imposed at specific growth stages [9], and tapered late-season irrigation [128]. These management options are interpreted within their respective crop and water-status conditions. The operational question is whether a locally calibrated schedule maintains marketable production while leaving a harvestable stand. Reduced late-season water may change crop condition and field access; joint machine measurements could clarify implications for feeding, separation, damage, and recovery. Scheduling must also respect cultivar response, soil storage, atmospheric demand, and the processor's quality specification.

Marouelli et al.'s final-irrigation experiment addresses processing-tomato yield, quality, and water-use efficiency [127]. The suitability of a 21-day irrigation cutoff remains dependent on the crop and environmental conditions of the experiment. A soil-water and crop-development interpretation is more useful than transferring a date across climates and soils. AquaCrop calibration and validation in tomato [129] support scenario analysis, which could be complemented by automatic valve-control and mechanical-harvestability trials. Before implementing a predicted cutoff, field observations should confirm root-zone water status, maturity composition, acceptable yield, and the intended harvest window; control must accommodate forecast and model uncertainty.

Ebert et al. compared four irrigation schedules in three commercially managed processing-tomato fields across 2020–2022 in Fresno County, using randomized blocks with three replicates [128]. The tapered schedule changed from 50% to 37% ETc after fruit set, followed by dry-down; the grower-practice control changed from 75% to 50% ETc. Reported seasonal irrigation savings for the tapered treatment were 10.1%, 7.3%, and 20.1%, respectively, with no significant yield differences among treatments within each season. The study's approximately 29% maximum saving was reported for the separate high-stress treatment. Cultivar and field changed between seasons, limiting separation of their effects. These water and crop-quality outcomes complement the stage-dependent Egyptian results [9]. Together, they support locally calibrated scheduling, with energy use and harvester losses providing useful additional endpoints.

Maturity composition is relevant to once-over harvest because green, acceptable ripe, and overripe or damaged fruit have different recovery and sorting implications. Figure 12

illustrates tomato maturity stages used in recognition research [43]. Related tomato studies [44,45] and the maturity review [27] address recognition; Lawal's ripe/unripe detector used 125 field images [45], offering a basis for independent season-long assessment of stand maturity. Rice harvest-period monitoring [46] is explicitly cross-crop. Representative field sampling linking estimated maturity composition with acceptable fruit and losses would support harvest timing and irrigation regulation. Combining visible maturity classes with fruit-firmness and detachment measurements could support calibration of suitable vibration settings.



Figure 12. Visual characteristics of tomato fruits at different maturity stages for machine vision [43].

Irrigation studies characterize water-management responses, mycorrhizal experiments examine crop responses under water scarcity [12], and maturity sensing estimates the distribution of ripening stages. Each contributes different information to preharvest decisions. Evidence of improved maturity synchronization or mechanical recovery depends on direct measurements of these outcomes. A workable feedback design would observe crop and soil state, recommend an irrigation or harvest action, execute it, and remeasure maturity, quality, soil access, and operational outcomes. This research pathway builds on the complementary contributions of irrigation, crop response, and sensing reviewed in this section. The irrigation savings reported by Ebert et al. are specific to the tested treatments and baseline [128]. Their implications for energy use, emissions, labor, economics, and harvester performance require separate measurements.

6. Low-Damage, High-Efficiency Mechanical Harvesting Technologies for Processing Tomato

6.1. Plant Cutting and Low-Damage Feeding

The intake system couples cutting, ground following, pickup, support, and transfer to the fruit–vine separator. Crop architecture and soil condition determine whether the header can acquire a continuous vine stream without leaving fruit on the ground. Tomato–handling analysis informs transfer design [130], while the chili-harvesting review [131] supplies complementary cross-crop concepts for tomato loss and capacity trials. Feed continuity provides an engineering target, with matching pickup rate to separation, cleaning, and sorting capacity supporting balanced material flow.

Machado et al. tested three GUARESI G-89/93 MS 40-inch harvesters (Guaresi S.p.A., Pilastri, Italy) in a 58-ha HEINZ 9553 field in Morrinhos, Brazil, at 125 days after transplanting [2]. Mean travel speed was 1.14 m/s; engine speed was 1900 rpm, and the manufacturer-specified shaker settings were 12 rpm and 2.5 Hz. Soil water content was reported as 20%, without specifying its basis. The electronic green-fruit/clod sorter was switched off, and workers selected the load. Seven 2.5-m^2 samples per machine and loss category yielded mean vine/ground/total losses of 2.55/3.70/6.25, 2.19/2.17/4.36, and 9.84/3.27/13.11 t/ha, respectively. These losses distinguish material acquisition from incomplete detachment and provide fixed-speed field benchmarks. Trials varying speed and machine condition could clarify their respective influences; further clarification of the differing machine-age interpretations in the abstract and conclusion would aid comparison. Cutting-height control and post-cut support offer candidate responses for follow-up evaluation. Research on leafy-green cutters examines cutting mechanisms [132], tea-stalk tests characterize bending behavior [133], and broccoli harvesting studies evaluate selective cutting end effectors [134]. These approaches could inform the design and calibration of tomato headers through crop-specific testing.

At the lift-to-separator transfer, a mismatch in conveyor direction, velocity, or support can increase relative motion and fruit contact [130]. Matching transfer trajectories, shortening unsupported drops, and limiting abrupt velocity changes are engineering responses to test. Slowing one conveyor alone can create accumulation and intermittent feeding. Their performance should be judged by vine mass flow, missed fruit, blockage and stoppage time, and fruit damage at the intended forward speed, rather than by an unloaded conveyor-speed setting.

Arazuri et al. found high-impact zones between cutting and color selection in five commercial processing-tomato harvester models in Navarre, Spain [6]. This supports checking transitions and receiving surfaces before increasing feed capacity. Compliant support and shorter drops are plausible ways to reduce impact exposure, with joint damage and throughput measurements clarifying their operational value. A flexible tobacco-leaf harvesting mechanism demonstrates a compliant design for handling leaves [135]. Tomato cushioning trials could investigate this design principle using measured fruit-damage outcomes.

Lodged or entangled vines and a dense canopy can cause uneven pickup and local feed surges. Header height, support geometry, and travel speed should therefore be matched to crop condition. Research on potato harvesting discusses pickup technologies [136], while development of a high-stem chrysanthemum harvester examines orderly crop guidance [137]. Their application to processing-tomato canopies could be explored through crop-specific trials. Where canopy variability is large, greater instantaneous conveyor capacity may be offset by transfer impact or downstream blockage; this relationship requires crop-specific field measurement.

Machado et al. distinguished vine-retained fruit from ground losses in a field comparison conducted at a fixed travel speed [2], providing a benchmark for subsequent trials of speed variation. For consistent comparison, effective field capacity is expressed as hectares harvested per elapsed operating hour (ha/h), while marketable-fruit throughput is expressed as tonnes of accepted fruit per elapsed hour (t/h). Including turns, blockage clearing, and unloading stops in the time boundary distinguishes these measures from theoretical or instantaneous capacity. Interpretation of feed mass flow (kg/s or t/h) also depends on whether the measured stream includes vines and impurities or fruit alone. Fuel or electricity per marketable tonne, crew-hours per hectare, and harvesting-plus-transport cost require consistent output and time boundaries. The cited comparisons [2,6,130–137] provide field- and component-level insights. Matched resource and economic measurements would complement rated-power and nominal-capacity information and support whole-operation assessment.

6.2. Low-Damage Fruit–Vine Separation

Fruit–vine separation balances ripe-fruit detachment with collision and impact exposure. Tomato loading tests characterize maturity-dependent resistance [4], while commercial processing-tomato observations identify damaging machine contacts [6]. Together, these contributions support adjustment of excitation and fruit removal to the harvested crop, with attachment strength and damage resistance treated as distinct properties.

Belt shakers oscillate a supported vine stream, whereas rotary shakers combine rotation with flexible fingers and excitation (Figure 13). Arazuri et al. examined both configurations across five commercial harvester models [6]. Their results support comparison by the location of damaging contacts and the response to model-specific adjustments; matched recovery, throughput, and energy measurements would further clarify the relative operating advantages.

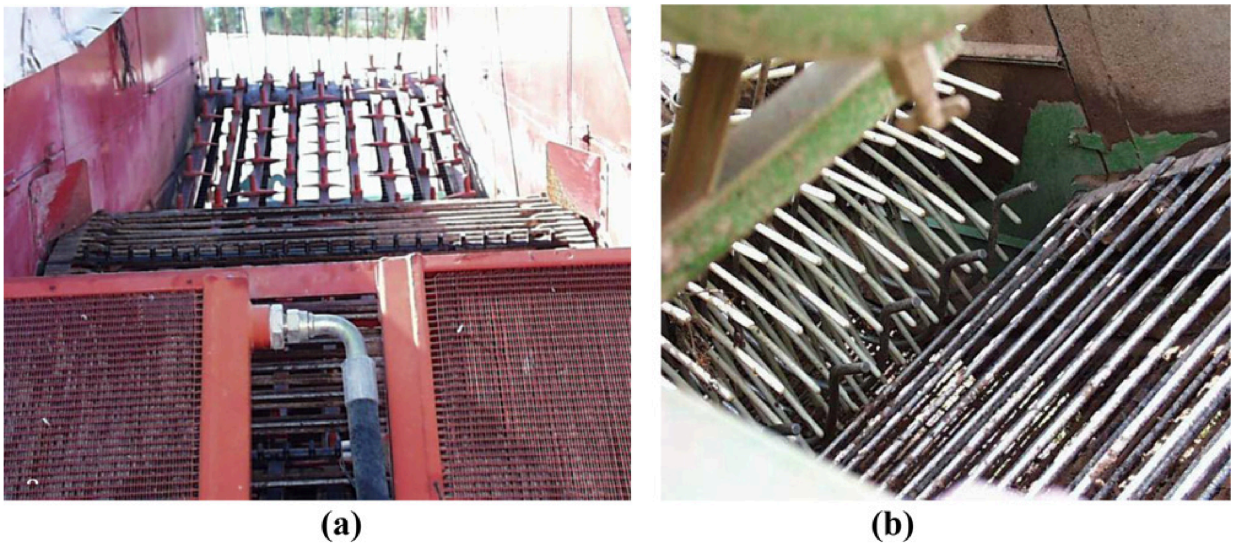


Figure 13. Belt-type and rotary fruit–vine separation devices for mechanical harvesting of processing tomato [6]. (**a**) Belt-type shaker, in which vibrating belts separate the fruit from the vines. (**b**) Rotary shaker, in which rotating flexible rods vibrate the plants to separate the fruit [6].

In Navarre, Spain, Arazuri et al. followed five commercial harvester models over four harvest years in processing tomatoes for peeling and concentration [6]. Samples of 30 fruit per treatment, test day, and machine distinguished skin cracks from deeper pulp breakage along the handling chain. Impact diagnosis led to reduced shaker speed in models D and E; discharge cushioning and lower drop or discharge velocity in A and

C; and these discharge changes plus lower travel speed in B. The authors summarized damage decreasing from approximately 20–29% to below 10%. This demonstrates the value of model-specific diagnosis under commercial conditions. Because the adjustments differed among models and years, the outcome characterizes the handling chain; isolated separator trials could establish the contribution of each excitation change.

Detachment and collision studies in other crops supply complementary methods: high-speed maize-threshing observations reveal contact dynamics [138], flax simulations describe material–drum interactions [139], and grape-cluster modeling incorporates vibration–collision coupling [140]. Applied to tomato-specific geometry and material properties, these approaches could help examine residence time and feed-layer effects. A dense vine layer may restrict excitation transmission, whereas repeated exposure can increase contacts; these proposed mechanisms can be tested against retained fruit, damage, and throughput.

The practical comparison is therefore between crop-specific operating envelopes rather than isolated separator settings. Attachment force, maturity and vine moisture can be paired with excitation, feed rate and residence time. Commercial impact observations favor prompt, cushioned removal of detached fruit [6], complemented by material-resistance measurements [4]. Joint recovery and immediate or delayed damage measurements would identify settings that preserve quality while sustaining output.

6.3. Mechanical Cleaning and High-Efficiency Impurity Removal

Mechanical cleaning removes physically separable stems, leaves, and loose contaminants before optical sorting. Airflow, screens, and material spreading exploit differences between fruit and residues, while selective optical rejection addresses green fruit, clods, and other targets [2]. This division of roles supports a continuous material flow, with cleaner inlet presentation reducing the burden on downstream sorting. The balance between residue removal and marketable-fruit recovery depends on incoming composition, moisture, and feed rate.

A rice field comparison illustrates the interaction between airflow distribution and loading [141]. With cultivar Zhen Dao 10, a 2.2-m cutting width, 57% straw moisture and 26% grain moisture, travel speeds of 0.5, 1.0 and 1.3 m/s corresponded to reported feed rates of 3.52, 7.05 and 9.16 kg/s. At 0.5 m/s, optimized versus conventional fans gave cleaning-loss rates of 0.60% versus 0.80% and grain-impurity rates of 1.81% versus 2.67%; at 1.3 m/s, the corresponding values were 1.34% versus 1.50% and 1.42% versus 1.83%. These field results favor feed-matched airflow distribution, with a smaller advantage at the higher loading. They provide a comparative method for tomato trials, whose fruit and wet-residue properties require their own calibration. Buckwheat CFD research offers an additional airflow-design approach [142].

Validation scope helps distinguish these cleaning contributions. Badretdinov et al. combined radial-fan CFD with airflow measurements across grain-cleaning sieves [18], identifying spatial variation useful for fan-layout assessment. By contrast, the buckwheat self-cleaning study evaluated airflow in an empty threshing unit, selecting an inlet condition relative to buckwheat suspension behavior [142]. These spatial and simulation methods complement the loaded rice field comparison. Tomato evaluation could combine them with measured residue distribution and fruit carry-out, allowing fan arrangement and speed to be selected for the actual feed rather than copied from grain settings.

Piezoelectric grain-loss sensing [143] and acoustic grain-impact identification [144] contribute approaches to monitoring rejected material. A tomato adaptation could distinguish wet-fruit impacts from vine and soil signals, then link calibrated loss estimates to bounded fan adjustments. Testing the resulting actuator response alongside recovered fruit, damage, and power demand would connect signal recognition with cleaning performance.

For tomato comparisons, a shared reporting basis can retain the source-specific grain definitions while specifying inlet feed, residue moisture, and sampling position. Retained impurity content can be expressed as impurity mass divided by collected-load mass, and marketable-fruit carry-out as rejected marketable-fruit mass divided by marketable-fruit mass entering cleaning. Count-based measures should be labeled separately.Co-reporting these outcomes with damage, elapsed-time throughput, and energy per marketable tonne would support a consistent harvesting assessment that integrates removal efficiency, crop quality, and resource use.

6.4. On-Board Optical Sorting and Quality Control

After mechanical cleaning, the optical sorter may still receive green or off-color fruit, surface-defective fruit, and residual clods that were not reliably removed by physical separation. Optical sorting therefore complements coarse cleaning through quality classification and targeted rejection. Material spreading, stable illumination, image acquisition, classification, and timed actuator diversion form a linked process. The reviewed machine-vision, multisensor, and visible–near-infrared studies [28,145–148] extend the available recognition and quality-sensing methods, providing image, laboratory, and prototype foundations for subsequent commercial on-board sorting validation.

Arjenaki et al.'s experimental CCD-camera sorter evaluated 210 tomatoes [147]. The publisher abstract reports defect-detection, shape-classification, and size-classification accuracies of 84.4%, 90.9%, and 94.5%, respectively, 90% overall system accuracy, and an estimated single-line capacity of 2517 fruit/h. These task-specific outcomes characterize prototype recognition and estimated capacity. Commercial on-board trials could add acceptable-fruit recovery and false-rejection measurements, with cultivar and field-feed conditions documented beyond the abstract-level description. Stable fruit presentation, illumination, and timely diversion provide useful priorities for that extension.

Arjenaki et al. used eccentricity to characterize shape, two-dimensional pixel area to estimate size, and average color components to assess maturity [147]; the study abstract also reports identification of visible defects. Complementary computational-cost and decision-latency measurements would clarify the operational implications of these descriptors. A useful comparison with learned detectors separates the classification task, sample composition, processing hardware, image latency, and confirmed diversion outcome to characterize the speed–performance balance of each approach under comparable conditions. Adapting to moving processing-tomato fruit also requires testing changes in illumination and presentation.

Hou et al.'s YOLOv8/OpenCV, Raspberry Pi, and robotic-arm prototype used 470 images (370 training, 50 test, and 50 validation) and 90 test tomatoes [145]. The reported 99.1% is the rounded mean of size, maturity, and defect-area accuracies; confirmed correct diversion would provide a complementary execution metric; ten throughput tests supported an estimated 1350 fruit/h. Dong et al.'s image-only MCS-YOLOv8 study [149] expanded 3255 images to 19,530 and reported a 15,624/1953/1953 training/test/validation split, with further detail on transformed-image allocation useful for assessing independence across sets. Under the reported common test environment (640 × 640-pixel input; NVIDIA GeForce RTX 3060 Ti GPU with 8 GB of video memory (NVIDIA Corporation, Santa Clara, CA, USA)), the source study reports MCS-YOLOv8 versus YOLOv8s precision of 91.2% versus 89.1%, recall of 90.2% versus 89.7%, mAP@0.5 of 90.3% versus 89.2%, and image times of 5.4 versus 4.2 ms. At mAP@0.5:0.95, the values were 82.2% versus 82.6%. These comparisons reveal a balance between gains at coarse IoU thresholds, inference time, and performance across evaluation metrics. They provide a basis for further actuator-throughput, on-board robustness, and cross-location trials. Figure 14 illustrates tomato

surface-quality recognition in the prototype study by Hou et al. [145]; validation of sorting under commercial field conditions remains necessary.

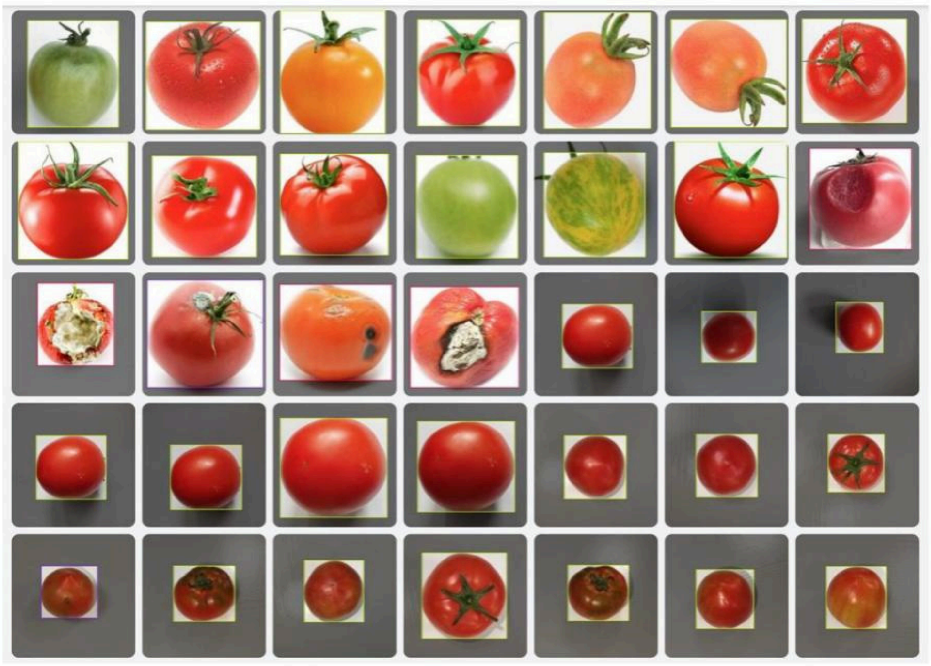


Figure 14. Examples of deep-learning-based tomato surface quality and defect recognition [145].

Putra and Rizaldi's gravity-fed color-sensor prototype was tested in an agricultural-engineering workshop [150], providing controlled-condition evidence for subsequent field-harvester evaluation. At a 12-degree slope, three runs of 60 tomatoes gave reported capacities of 126.7, 135.4, and 137.1 kg/h (mean 133.1 kg/h); color-sort conformity was 80.0%, 78.3%, and 83.3%. Ripe and half-ripe fruit were stored at room temperature for three days after sorting before discoloration and physical changes were assessed; reported damaged-fruit proportions were 23.3% and 10%, respectively. These post-storage observations complement immediate-rupture assessment. Capacity is retained as author-reported, with clarification of sample mass units and cultivar useful for independent normalization and transfer. Its color conformity and delayed-damage measures differ from the mean attribute accuracy reported by Hou et al. [145] and the estimated fruit-count capacity reported by Arjenaki et al. [147]. Combining image processing with weight measurements offers an additional tomato-sorting approach [148], while a review of nondestructive fruit-quality detection summarizes other sensing technologies [29]. Matched commercial trials could compare these approaches using damage, recovered acceptable fruit, throughput, and cost.

Internal-quality prediction is distinct from surface classification. Égei et al.'s Hungarian processing-tomato study [146] used 132 intact red-ripe H1015 and UG812J samples, with 99 calibration and 33 validation observations; its cross-validation errors for SSC were 0.58–0.59 degrees Brix, characterizing composition prediction, complementing rejection-rate and field-control measurements in future integrated trials. Reviews of infrared spectroscopy [151] and agricultural X-ray inspection [152] describe methods for evaluating internal quality. Their application in on-board tomato systems could be explored through dedicated calibration and validation. In the 2012 Hungarian field experiment of Szuvandzsiev et al. [153], five processing-tomato hybrids supplied 64 puree samples. Spectra were acquired over 325–1075 nm, smoothed over a retained 530–1000-nm interval, and restricted to 550–975 nm for first-derivative modeling. Three outliers were removed; the remaining 61 samples were modeled for SSC, lycopene, and polyphenols using leave-one-out cross-validation, without an independent prediction test set. These results suggest

potential destructive-sample screening at processing reception. Commercial reception trials, intact-fruit non-destructive inspection, and concentrated-paste mid-infrared testing offer distinct directions for further study. Matched samples, analytes, and validation procedures would support comparisons between intact-fruit and puree measurements.

Spatially resolved spectroscopy can distinguish optical absorption from scattering and provide information on tissue properties at different depths, as reviewed by Xia et al. [154]. It offers a potential complement to surface imaging, with calibration and fruit-presentation trials supporting exploration of on-board tomato-harvester maturity control. The processing-tomato measurements by Égei et al. support composition estimation within the tested sample set [146]. Shelf-life prediction, condition-specific firmness criteria, and autonomous rejection of moving field fruit offer further applications for dedicated calibration and validation.

Image-only detection [149], actuator-linked prototypes [145,148,150], and composition prediction [146,151–154] address complementary functions and test scopes, favoring comparisons organized by task and operating context. For recommended operational reporting, false rejection is acceptable fruit rejected divided by acceptable fruit entering the sorter; missed rejection is unacceptable fruit retained divided by unacceptable fruit entering. Both require a stated ground truth, a sampling point, and a consistent count- or mass-based basis. Fruit/h and kg/h should remain separate unless measured fruit masses support conversion; elapsed-time throughput should include stated stoppages. Immediate rupture, three-day post-sort injury [150], and quality-prediction error measure different endpoints. Cultivar, maturity mix, illumination, overlap, feed moisture, and actuator timing should accompany the results. Matched commercial on-board energy, crew-demand, and cost measurements would extend assessment of these approaches.

6.5. Low-Damage Fruit Collection and Unloading

After sorting, transfer contacts and accumulation can cause additional injury. Tomato injury and bruising experiments [5,155] are more directly relevant to contact loading than Zheng et al.'s individual cluster-tomato grasping simulation [156], which contributes an individual-fruit contact model for consideration alongside bulk receiving and unloading trials. Studies of grape compression and hanging-force mechanics offer additional approaches to examining load response and handling [157,158]. Their use in bulk tomato handling would require crop-specific evaluation. Compliant receiving, controlled relative velocity, and shorter drops should therefore be evaluated against tomato-specific handling and transport observations, with the gripper simulation informing contact design within its individual-fruit scope.

Zu et al.'s net-bag prototype (Figure 15) offers a controlled individual-fruit comparison [159] that could inform cushioning studies for bulk combine unloading. The greenhouse cultivar Sheng Luo Lan 3689 supplied 100 turning-stage and 100 red-ripe fruit, each maturity group divided into five groups of 20. Fruit diameter was 66.5 $\pm$ 3 mm; release was 60 mm above the support rod, conveyor rotational speed was 9 rpm, and room temperature was 20 $\pm$ 5 degrees C. Release and net unloading involved manual actions, and deterioration was checked every 0.5 days. Turning-fruit shelf life averaged 16 days in the unhandled control, 15.7 with the net, and 14.7 without it; corresponding red-ripe values were 5.5, 4.98, and 3.74 days. The reported 1.9% and 9.5% damage indices describe relative shelf-life reduction from the respective controls, providing a delayed-quality endpoint complementary to visible-damage counts. Cushioning improved this device-specific outcome; bulk-throughput, commercial unloading-cost, and drop-height trials could extend its application.

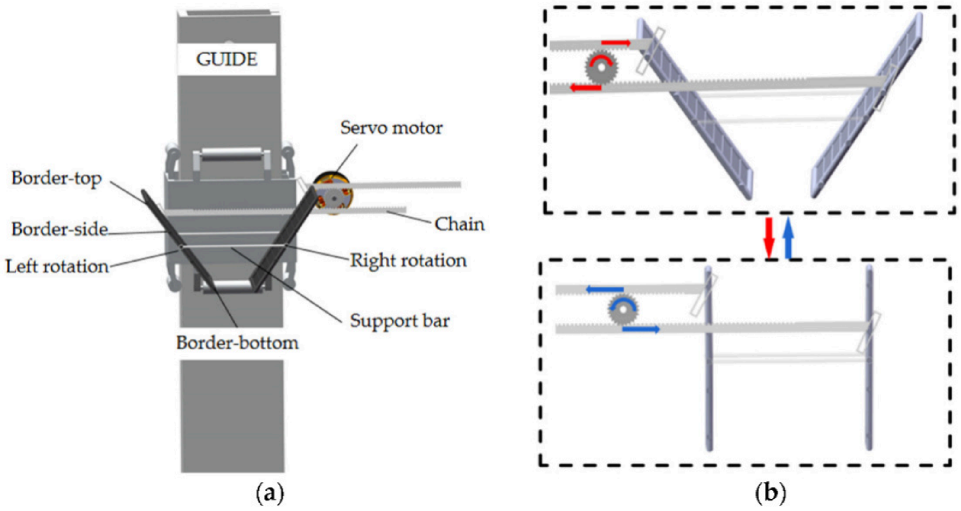


Figure 15. Structure and working principle of a flexible net-bag cushioning mechanism for tomato collection [159]. (**a**) Main components and structural arrangement of the net-bag mechanism. (**b**) Opening-and-closing principle of the net bag. The red and blue arrows indicate the two opposite directions of rack-and-gear movement, and the vertical arrows indicate the transition between the V-shaped receiving state and the Λ-shaped unloading state [159].

Bulk collection exposes fruit to loading, transport, and waiting conditions that should be assessed together. A Brazilian industrial-tomato study compared manual harvest, mechanical harvest, and subsequent transport, and sampled transported fruit by container, position, depth, and removal time [36]. It measured firmness and other quality attributes in one farm and hybrid; these observations provide quality references that could be complemented by pile-pressure and depth trials. Loading height, layer distribution, vibration, and waiting time should therefore be recorded alongside immediate damage and subsequent quality loss. Reducing accumulation and coordinating unloading offer candidate engineering responses for follow-up continuous-unloading comparisons.

Field observations of industrial-tomato harvesting and transport relate handling stages to measured fruit quality [36]. A synthesis of tomato softening mechanisms describes cell-wall disassembly and biochemical regulation, providing a biological basis for interpreting maturity-dependent handling response [160]. Controlled loading studies contribute complementary exposure-specific evidence. The Deborah-tomato experiment [5] imposed a 1.2-m drop, a 3-kg compressive load for 15 min, or a cutting injury, followed by 15 days at 25 ± 1 degrees C and 80 ± 5% relative humidity. It supports relating imposed loading to delayed firmness change. Matched trials across green and red fruit, along with recorded vehicle vibration, could extend these results to maturity-specific transport responses.

The most relevant comparisons for collection are the controlled tomato load treatments [5,155], the with/without-net individual-fruit trial [159], and industrial harvest/transport observations [36]. They measure imposed injury, relative shelf-life change, and handling-associated quality, respectively; grape-handling studies provide complementary mechanical analogies [157,158], and tomato-softening synthesis adds tissue-level context [160]. Together, these studies provide a foundation for matched tests of continuous and intermittent bulk unloading. Such a test should report fruit maturity and firmness, pile depth and receiving geometry, transfer count, drop distribution, waiting time, and vibration exposure. Immediate rupture and delayed quality loss need separate observation periods. The existing evidence supports evaluation of cushioning and logistics; complementary bulk-throughput, fuel, crew-demand, transport-cost, and accumulation measurements could guide operational selection.

6.6. Coordinated Control of Harvesting Parameters

Travel speed, vine feed rate, separator exposure, cleaning load, sorter presentation, and unloading availability form a coupled system. A higher forward speed may raise instantaneous intake but overload a later stage or increase stoppages. A rice-loss monitor combines piezoelectric impact signals with decision-tree classification and was calibrated on a bench across grain–impurity mixtures and moisture conditions [21]. This quality-feedback measurement complements intake estimation. Tomato-specific sensor calibration and paired loss measurements could connect travel-speed adjustments with recovered-fruit outcomes. The control objective should be marketable fruit recovered per elapsed operating time subject to loss, damage, impurity, and energy limits. Demonstrating that objective requires measurements across the actual harvester chain rather than independent component settings.

Machine-condition effects should be interpreted with the test design. In the HEINZ 9553 comparison [2], machines with 8762, 5787, and 5222 accumulated hours shared nominal operating settings, but total losses were 6.25, 4.36, and 13.11 t/ha. The lowest-hour machine therefore had the largest measured total loss; vine loss contributed most to that result. The oldest machine had a larger overall-defect proportion than the lowest-hour machine. These observations highlight variation among machines and motivate trials separating accumulated hours, wear, operator, and crop influences. Clarifying the differing interpretations in the abstract and conclusion would further aid comparison. Condition monitoring could support maintenance and adjustment calibrated to each machine. Research on the influence of vibration on grain-flow sensing examines sensor disturbance and its mitigation [161]. These methods could inform sensor testing in tomato-harvester condition monitoring.

The Navarre impact-recorder study [6] demonstrates diagnosis followed by model-specific operator adjustments and cushioning modifications over four harvest periods. Its reduced damage result demonstrates the value of targeted intervention and provides a practical foundation for subsequent automatic disturbance-response and closed-loop trials. Machine-vision sampling of rice kernels provides a complementary quality-measurement route: a controlled study compared broken/whole-kernel recognition with manual classification [162]. Adapting the sampling and reference-measurement design to tomatoes would allow assessment of visible injury under changing material presentation. A tomato closed loop could build on these measurements by selecting and executing an action, then using observed loss or damage to guide subsequent adjustment under changing feed conditions.

Broad-bean harvesting research examines self-adaptive control [22]. In plant protection, a 28-m spray-boom system combined ultrasonic and inertial measurements with electro-hydraulic active suspension; bench disturbance tests and a field trial at 4 km/h evaluated roll-angle response [23]. These studies illustrate adaptive operating control and measured attitude feedback with different control objects. Tomato-specific system identification can build on these architectures to relate harvest commands to material response and product-quality outcomes. For tomatoes, joint recovery, damage, cleaning-load, and sorting-demand measurements would help identify separator adjustments within an acceptable operating region. Validation of the architecture at whole-harvester scale requires repeated field disturbance tests and independent evaluation of the crop–machine system.

Coordinated control should also extend to fruit collection and unloading. Industrial-tomato harvest and transport measurements include firmness, fresh-mass loss, transport vibration, and fruit sampling position and time [36]; they support evaluating logistics and quality together and could inform synchronized harvester–truck control trials. Consequently, when the collection system approaches capacity or transport vehicles are not synchronized with the harvester, maintaining a high feed rate may not increase effective system throughput and may instead increase accumulation and subsequent quality loss. Whole-machine control

should link unloading demand to the upstream operating rate and, when necessary, adjust travel and conveying speeds to keep the harvester and transport vehicles synchronized [24].

Bench and field comparisons of motor-driven maize seed meters relate forward-speed commands to measured seed-spacing uniformity [163]. This actuator-to-outcome comparison provides a method for evaluating crop-specific drive responses. Commercial tomato impact diagnosis [6], actuator-linked sorting prototypes [145,150], rice-loss and breakage measurements [21,162], broad-bean adaptive harvesting [22], spray-boom attitude feedback [23], and grain-flow sensing [161] contribute distinct functions and verification contexts. Whole-machine tomato coordination offers a further research direction, linking automatic position or speed commands with measured recovered yield and fruit quality to develop outcome-based feedback.

The available comparisons support condition-specific controller and parameter selection, with joint evaluation of recovery, throughput, damage, impurities, energy, labor, and cost guiding multi-objective development. Tomato field observations [2,6,36] should anchor performance interpretation; component simulations, recognition models, and cross-crop controllers provide supporting methods with narrower claims. Trials should report cultivar, maturity distribution, vine/fruit/soil moisture, equipment condition, feed composition, and denominators for loss and damage. Technical maturity can be described through documented commercial operation, instrumented field evaluation, prototype actuation, and simulation, with numerical readiness assessment reserved for a defined evaluation protocol. Tables 5 and 6 organize the comparable outputs and conditional trade-offs; matched fuel, crew-hour, cost-per-marketable-tonne, and whole-field closed-loop measurements offer priorities for extending these comparisons.

Table 5. Reported mechanical-harvesting outcomes, test conditions, and evidence boundaries. NR denotes an outcome awaiting matched processing-tomato measurement in the cited examples. Values retain the original study units and definitions, supporting interpretation within each row's test context.

Subsystem	Test Conditions/Route	Reported Outcomes	Central Trade-Off	Evidence Boundary
Cutting and feeding	HEINZ 9553; 3 machines; 1.14 m/s; sorter off [2]	Vine/ground loss: 2.55/3.70; 2.19/2.17; 9.84/3.27 t/ha [2]	Capacity versus layer fluctuation and impact	Seven 2.5-m^2 samples per loss category and machine; fixed-speed comparison
Fruit–vine separation	Five commercial models; four harvest years; model-specific adjustments [6]	Reported damage: 20–29% to <10% after combined interventions [6]	Complete detachment versus repeated collision	Model-specific field results; matched belt/rotary throughput and fuel trials would extend comparison
Mechanical cleaning	Grain airflow/CFD/loss-sensing methods [18,141–144]	Matched tomato impurity, fruit-loss, damage and energy results: NR	Cleanliness versus fruit loss and power	Cross-crop methods offer a basis for matched tomato trials
Optical sorting	Robot: 90-fruit test [145]; gravity: three 60-fruit runs at 12° [150]	Estimated 1350 fruit/h [145]; reported 133.1 kg/h; 3-day damage 23.3%/10% [150]	Recognition quality versus line throughput	Task-specific results; tomato-image detection has been evaluated [149]; sorter trials could assess execution
Collection and unloading	Greenhouse fruit; 60-mm release; 9-rpm conveyor; 20 ± 5 °C [159]	Shelf life with/without net: 15.7/14.7 d turning; 4.98/3.74 d red [159]	Rapid transfer versus cumulative loading	Individual-fruit cushioning tests; industrial-tomato transport observations inform bulk-handling trials [36]
Whole harvester	Same-model fixed-speed trial [2]; multi-year operator intervention [6]	Total loss 6.25/4.36/13.11 t/ha [2]; matched fuel, crew and cost: NR	Multiobjective acceptable region	Cultivar-, year-, and endpoint-specific results guide whole-harvester closed-loop trials

Table 6. Parameter changes, intended benefits, side effects, and verification criteria.

Parameter Change	Intended Benefit	Likely Side Effect	Required Co-Measurement	Verification Criterion
Increase travel/feed speed	Higher area and mass throughput	Thicker, less uniform layer; blockage; downstream overload	Instantaneous feed, loss, damage, impurities, energy	Capacity gain while every threshold remains satisfied
Increase separator excitation/exposure	Higher fruit detachment	Repeated impacts and ripe-fruit damage	Detachment, impact dose, immediate and latent damage	Minimum action meeting detachment target below damage limit
Increase cleaning intensity	Lower leaf, stem, and soil contamination	Fruit carry-over, collision, and power demand	Impurity classes, fruit loss, damage, energy per tonne	Net cleanliness gain without exceeding loss/energy limits
Increase sorting-belt speed	Higher nominal sorter capacity	Overlap, reduced exposure, timing error	Object spacing, miss/false rejection, actual capacity	Stable true sorting rate under representative feed
Reduce drop height/add compliance	Lower peak impact and rupture risk	Possible accumulation or reduced discharge rate	Impact distribution, queue depth, damage, throughput	Damage reduction without persistent bottleneck
Increase pile depth/loading rate	Fewer interruptions and faster logistics	Compression, heat, vibration exposure	Pressure, residence time, delayed quality, logistics rate	Marketable quality retained through delivery

7. Mechanized Postharvest Handling Technologies for Processing Tomato Vine Residues

7.1. Vine-Residue Discharge and Regulation of Field Distribution

Residue handling links crop properties to treatment requirements, mechanical operations, transport and storage, and final utilization. Processing-tomato vines discharged behind a harvester can form uneven layers or entangled windrows, changing the feed presented to downstream equipment. Concentrating material may simplify collection but overload a pickup unit; spreading it may facilitate incorporation but increase the area from which material must be recovered. Cross-crop residue studies provide design analogies [25,164], while wheat-residue remote sensing provides a way to assess surface cover [165]. These contributions provide a basis for tomato-specific trials of discharge geometry and downstream recovery. Route comparisons should use both one hectare treated and one tonne of residue dry matter delivered at a specified moisture and contamination level, because area coverage and usable-feedstock recovery answer different questions.

For off-field recovery, matching continuous windrows to pickup width supports steady feed delivery. Directional discharge offers an alternative where selected field zones must remain clear. In ratoon rice, a guide device directed chopped residue toward the wheel-rolling zone; field tests reported 95.2% of residue mass in the designated zone [164]. This landing-zone measure characterizes directed discharge, with spreading uniformity, tomato pickup efficiency, and energy use offering complementary endpoints for adaptation. For tomato vines, outlet width and guide geometry require validation against vine loading, windrow depth, downstream interruptions, and recovered dry matter.

For direct incorporation, discharge should match the working width and acceptable feed layer of the tillage implement. Sentinel-2B and Landsat-8 imagery have been used to map wheat-residue surface cover [165]. This mapping approach could support residue-distribution assessment alongside measurements of discharge-device performance,

blockage, decomposition, and soil nutrient response. A fan or deflector may alter distribution [25,164]; including its additional drive requirement, plugging risk, and maintenance would complete the operational comparison. Matched fuel and work-quality baselines would clarify whether wider spreading or fewer downstream passes improve total energy use.

Where specific field zones must be avoided, directional discharge provides a third option, but its outlet geometry and landing zone should be matched to the receiving width and feed requirements of the downstream machine.

Discharge should therefore be assessed as an upstream feed-conditioning operation. Useful measures are windrow width and depth, spatial cover, downstream feed fluctuations, interruptions, and recovered residue. Recovery should state whether its denominator is initial available dry matter or collected plus uncollected material; soil and plastic contamination require separate mass fractions. Fuel per hectare and energy per delivered dry tonne should include the discharge device and subsequent treatment. The cross-crop examples inform discharge and distribution assessment [25,164,165], providing a starting point for tomato-vine swath-width and sustainability trials.

7.2. Mechanized Chopping and Soil Incorporation of Vine Residues

Ground-hugging, entangled vines require controlled presentation to the cutter as well as sharp blades. A sweet-potato-vine rotary-cutting bench illustrates the distinction between component power and field performance [166]. With cultivar Shinshu 19, a rotor speed of 1266 rpm, a conveying speed of 0.54 m/s, and a 1.0 kg feed batch, five validation runs yielded a mean torque of 0.85 N m and a cutting power of 146.2 W. The batch mass describes the test loading, with continuous mass-flow measurements offering a complementary operating metric. These laboratory results support study of feeding–cutter interactions and could guide tomato-vine field-capacity, moisture-response, and double-roller harvester trials.

A side-sweeping maize-straw cutting and crushing device provides a field-tested comparison [167]. At a tractor speed of 1.6 m/s, with field measurements repeated twice, the test reported 94.22% qualification against the study's crushed-length criterion, 17.21% scattering unevenness, 0.81% missed cutting, and 42 mm stubble height. The corresponding bench qualification was 92.23%, providing a separate controlled-condition reference alongside the field result. These outcomes characterize harvested maize straw under the authors' cutting and distribution definitions. Additional residue-moisture records would support matched tomato comparisons, while whole-chain fuel and greenhouse-gas measurements could extend the operational assessment. Cutter selection should balance the required length distribution against missed cutting, distribution, soil contact, and wear.

Supported cutting offers a different engineering response. A press-wheel-assisted coulter mechanism was tested on rice residue in a clay-loam soil bin at 2.5 km/h and a 15 mm cutting depth [168]. This simulated-field component test contributes evidence on restraint, cutting, clogging, and power, complementing future field trials of constant-cam or reciprocating choppers. Clarification of the differing residue-loading values in the abstract and optimization table would support subsequent calibration of operating settings. Together with the rotary bench and maize field studies [166,167], it illustrates alternative ways to stabilize material at the cutting interface. Direct comparison requires matched moisture, loading, length criteria, and measurement boundaries.

Combined chopping and incorporation can remove a process transition, with the additional tillage load included in total energy assessment. A paddy-residue chopping–rotary-tillage study used a 2.1 m implement and a 55.95 kW tractor with residue loading of 8–9.5 t/ha and reported residue moisture of 22–30%, without a clear moisture

basis [169]. Across its tested settings, fuel use was 12.5–14 L/h and actual field capacity was 0.26–0.35 ha/h. These separately reported ranges describe hourly fuel use and field capacity; paired observations would allow calculation of fuel per hectare. The study demonstrates combined treatment, offering a basis for matched comparisons with separate operations and subsequent tomato-specific calibration. Figure 16 shows the integrated equipment.

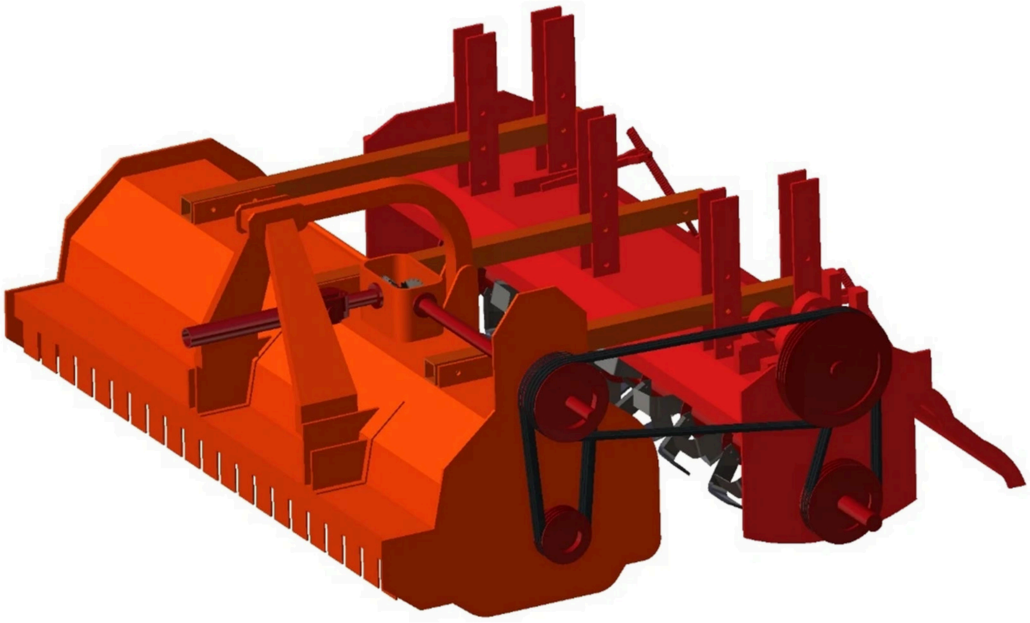


Figure 16. Integrated residue chopping–rotary tillage incorporation machine [169]. Colors are used only to visually distinguish machine components [169].

The reviewed chopping examples span a vine-cutting bench, a maize field machine, a rice soil-bin mechanism, and a paddy chopping–incorporation implement [166–169]. Their power, fuel, length-qualification, and field-capacity results provide complementary references for comparisons organized by material and test scale. A cucumber-straw study compared discrete-element predictions with hammer-mill measurements on naturally dried Jasper No.2 residues, using a 4-mm sieve and reported 18% moisture content, whose basis was not specified [170]. Measured energy per input tonne increased when a larger hammer–screen gap caused clogging, illustrating the value of pairing size-reduction models with actual screening and energy measurements. These conditions support a material-specific grinding comparison rather than a universal tomato-vine setting. In the sweet-potato bench study, torque and power responded differently to rotor speed [166], highlighting the value of evaluating both measures. For tomato vines, the relevant target is a downstream-compatible particle-size distribution at acceptable recovery, contamination, and total energy per delivered dry tonne. Smaller particles can improve mixing but add cutting work or complicate fiber separation; their value depends on the receiving process. Matched field energy, labor, maintenance, and cost measurements would broaden assessment of these approaches.

7.3. Mechanized Pickup and Collection of Vine Residues

Linking collection with subsequent packaging and transport supports assessment of the complete recovery route. In a 2019 Swedish wheat trial with three replicated plots per treatment, chaff was either collected loose in a trailer or added to the straw swath for baling [171]. This comparison of alternative logistics provides a basis for tomato pickup and life-cycle studies. The logistics comparison can be extended through dedicated trials of detached tomato-vine pickup and plastic-film separation. For tomato fields, recovery

should be tested alongside soil entrainment, retained surface residue, clogging, and ground traffic, with the intended destination stated.

Pickup fingers or tines lift residue while conveyors meter it to a chopper or bin. This sequence can separate acquisition from size reduction, with feedstock-cleanliness measurements complementing collection efficiency [25]. A rice-straw pickup–chopping machine tested at 25% straw moisture on a wet basis and 8–12 cm stubble height provides a concrete example [172]. Collection efficiency was defined as collected mass divided by collected plus uncollected mass; chopping quality was the mass share in the 15–30 mm length interval. Retaining these definitions supports comparison of the reported results, while dry-matter recovery after cleaning offers a separate downstream metric.

Within that rice study, fixing knife speed at 2400 rpm and elevator speed at 1.10 m/s while increasing travel speed from 1.3 to 2.2 km/h reduced collection efficiency from 98.00% to 95.27% and the 15–30 mm fraction from 85% to 70% [172]. This within-study comparison demonstrates a speed–recovery–size-quality trade-off under the stated straw and stubble conditions. The measured range provides a reference for tomato-specific recovery trials. Wet tomato vines, soil clods, and plastic contamination require separate tests of pickup height, feed loading, conveyance, and interruptions.

Integrated pickup–chopping–loading reduces transfers, while retaining separate constraints on cutting and collection. Tests of a rice-residue crushing-and-throwing device examine material handling [17]. Tomato-vine trials could extend this assessment by measuring compression, rebound, and binding performance. The pickup–chopping study estimated an integrated cost of USD 102.82/ha against an assumed separate pickup/baling, field-edge transport, and stationary-chopping total of USD 205/ha [172]. This cost-model comparison estimates an integration benefit under stated assumptions: the estimate assumes 200 operating hours/year, a ten-year machine life, and diesel at USD 0.44/L, and excludes long-haul transport, storage, and conversion. Clarifying the reported field-capacity units would facilitate independent normalization of the cost estimates. Local utilization and full-chain cost assessments would support selection of a suitable recovery route.

For field collection, clean material delivered to a useful destination provides an end-use-oriented performance measure. Cereal-residue logistics and pickup studies provide methods for recovery-route assessment [25,171,172]. Tomato-specific comparisons can build on these methods by measuring recovered dry matter, uncollected residue, soil and plastic fractions, interruptions, fuel per hectare, and energy per delivered dry tonne. Extra collection traffic may increase compaction risk, and removal changes the material retained for soil cover and organic-matter inputs; site-specific measurements would clarify these soil and recovery outcomes. Equipment cost, seasonal labor, maintenance, annual use, receiving capacity, and transport distance determine whether integrated or separate handling is viable. The cited cereal evidence offers a starting point for processing-tomato trials of these selection criteria.

7.4. Compression and Baling of Vine Residues

Compression and baling reduce the volume of residues before off-field transport, but machine choice depends on feedstock condition and package requirements. A technical synthesis of biomass baling distinguishes reciprocating-plunger square balers from fixed- and variable-chamber round balers; fixed chambers generally produce a softer core, whereas variable chambers form a denser core from the start [173]. The chapter separates power take-off demand from drawbar demand and relates compaction pressure to density and specific energy. These engineering principles and secondary evidence from other biomass provide a foundation for processing-tomato residue trials. Square and round systems should therefore be compared using feed moisture, mass throughput, package

geometry, density, binding integrity, and handling losses under matched conditions. Higher density may improve volume use but add compaction work or alter storage requirements. Tomato-vine pressure, rebound, and bale-geometry trials could translate these principles into crop-specific settings.

Compression, bale formation, and wrapping need separate evidence. A rice-straw study tested wrapping of already formed cylindrical bales, 500 mm in diameter and 750 mm long [174]. For four-layer wrapping, six parameter combinations (31–32 rpm tumbler speed, a 2.6 speed ratio, and 20–22 N film preload), each repeated ten times, produced measured wrapping times of 37.2–38.3 s/bale and film consumption of 3.19–3.41 kg/t of bale mass. Timing began at motor start for the wrapping operation; loading, unloading, transport, and the complete work cycle were outside this endpoint. These values characterize wrapping time and film use on the study's bale-mass basis. They provide references for packaging trials, with dry-tonne transport energy, compression density, tomato-vine baling rate, pressure, rebound, and binding integrity offering complementary crop-specific measurements.

The same rice study compared four, five, and six film layers during 45 days of ambient storage, using 100 inoculated fresh-rice-straw bales per group [174]. Reported pH values were 4.07, 3.98, and 3.79, respectively, while neutral-detergent fiber, acid-detergent fiber, and crude protein did not differ significantly. This supports condition-specific assessment of sealing and silage quality, offering a reference for dedicated tomato-vine storage and feed-safety studies. Film manufacture, collection, and end-of-life treatment add material and environmental burdens. Wrapping should therefore be justified by the receiving process and storage-loss comparison, rather than adopted solely to retain a dense package.

For processing tomato, compression trials should report initial moisture and its basis, chamber loading, pressure or force, final bulk density, rebound after release, binding failures, and energy per dry tonne. The biomass-baling synthesis provides the engineering basis for separating compaction and traction loads [173], whereas the rice experiment measures wrapping and subsequent storage of preformed bales [174]. Together, these contributions could guide matched tomato-vine compression and packaging trials. Handling trials should measure breakage, loading time, vehicle payload and volume use, and dry-matter loss over a stated storage duration. Greater density may reduce volume-limited journeys but add compaction, wrapping, bale-opening, or drying work; the balance depends on distance, payload limits, storage conditions, and annual equipment utilization. Tomato-specific density targets and transport break-even distances offer useful priorities for field and logistics evaluation.

7.5. Resource Utilization of Vine Residues

Postharvest processing tomato vine residues consist mainly of stems, leaves, and a small amount of unharvested fruit. Their valorization potential depends on the downstream utilization route, and different routes impose different requirements on upstream mechanical treatment. Vine residues are rich in lignocellulosic components such as cellulose and hemicellulose, while moisture content, C:N ratio, and ash content vary with plant organ and growing conditions. Treatment assessment can combine chopping intensity and collection completeness with feedstock quality and the requirements of the receiving process. Current valorization routes include composting and organic-fertilizer production, anaerobic digestion, biomass energy, and fiber-based materials; upstream mechanical operations should consequently move from generic volume reduction toward end-use-oriented feedstock pretreatment [175,176].

Soil-amendment response and residue-processing performance provide complementary perspectives on valorization. A two-year field experiment with industrial tomato Coronel F1 across three soil textures found higher yield under mineral fertilizer than compost

alone, but higher soluble solids under compost, illustrating a yield–quality trade-off [177]. This crop-response evidence complements studies of tomato-vine compost production. Direct tomato-residue studies address other endpoints: laboratory composting in three 200 L drums rotating at 3 rpm, with approximately 1 cm tomato residues mixed with chicken manure, generated about 1.9 MJ/kg organic matter as biological heat over the 107-h analysis period, of which 96% was lost in the reported heat balance [178]. This generated-heat estimate describes the analysis period; recovered energy and full-cycle net energy provide complementary measures for subsequent assessment. A separate study assessed nutrient and germination indices after 65 days of tomato-straw composting followed by 35 days of pot-scale vermicomposting at specified substrate and worm loadings [179]. These quality outcomes provide a basis for complementary assessment of mechanized recovery and net greenhouse-gas effects.

Anaerobic digestion depends on feed preparation, inoculation, and reactor conditions rather than a universal field grinding target. Zhu et al. used tomato stems and leaves dried at 65 °C and ground in the laboratory; triplicate 70-day batch tests in 1 L bottles contained 80 g dry residue, 520 mL water, and 200 mL inoculum [180]. The finest tested fraction (<0.15 mm) at 35 °C produced the highest cumulative biogas volume among the tested fractions under those batch conditions. Their one-year desert pilot used a 700 L digester and prepared feed averaging 0.8 ± 0.4 mm. These tomato-residue digestion tests provide a basis for comparing feed preparation options and their net energy implications in field-to-digester systems. A separate tomato-bio-waste study used 37 °C batch tests in 125 mL bottles with 40 mL liquid and continuous trials in 5 L stirred reactors with feed below 2 mm [181]. Continuous performance diverged from batch response, with antimicrobial compounds including tomatine investigated as possible constraints. Interpreting batch particle-size responses and continuous co-digestion results within their respective feed and loading conditions supports process comparison. Including drying, grinding, water use, reactor heating and mixing, storage, and digestate management would connect gas-production results with net energy and emissions assessment.

Sustainability comparisons need a stated baseline and system boundary. A common basis for residue availability and final services supports comparing direct field incorporation with off-field composting or digestion. A consistent reporting basis would express fuel use in L/ha, energy in MJ or kWh per delivered dry tonne, labor in hours per hectare or dry tonne, and costs on the same basis. Moisture, contamination, transport distance, annual equipment use, and price year define the comparison conditions. The system boundary encompasses chopping, collection, densification, transport, storage, conversion, maintenance, and capital allocation. Explicit assumptions and separate accounting of soil effects and displaced fertilizer or energy would help preserve a consistent balance. Measuring total energy alongside pass reductions would connect process changes with net resource outcomes.

Thermochemical and fiber routes impose different constraints. Moisture increases drying demand, and entrained soil contributes ash; these feedstock-quality considerations in the cited review [175] motivate tomato-chain measurements of drying and conversion energy. Fiber applications require cleaner, compositionally consistent material so that selective collection may be more useful than indiscriminate grinding. Its added sorting and handling work still needs measurement. Stem-and-leaf glycoalkaloids also require a specific safety assessment before feed use [175,181]; compositional analysis can be complemented by safety and feeding assessments to guide suitability. A comparative assessment of material, energy, and emissions flows would extend the technical feasibility of fiber or energy conversion to include environmental outcomes.

Collection and storage should preserve the material attributes required by the selected use. Direct incorporation avoids off-field transport, whereas centralized routes may require volume reduction, vehicle loading, storage, bale opening, and further cleaning; measuring the associated costs and losses would support full-route comparison. Figure 17 presents a conceptual cascade based on a tomato-residue review [176], offering a framework for future whole-chain energy and emissions comparisons. Food-ingredient fractionation of organic tomato-processing by-products [182] contributes fruit-derived material evidence, with field-vine food or feed applications calling for separate suitability and safety assessments. Cascading is a potential route whose value depends on fraction yields, contamination, separation and drying energy, markets, and treatment of the remaining material.

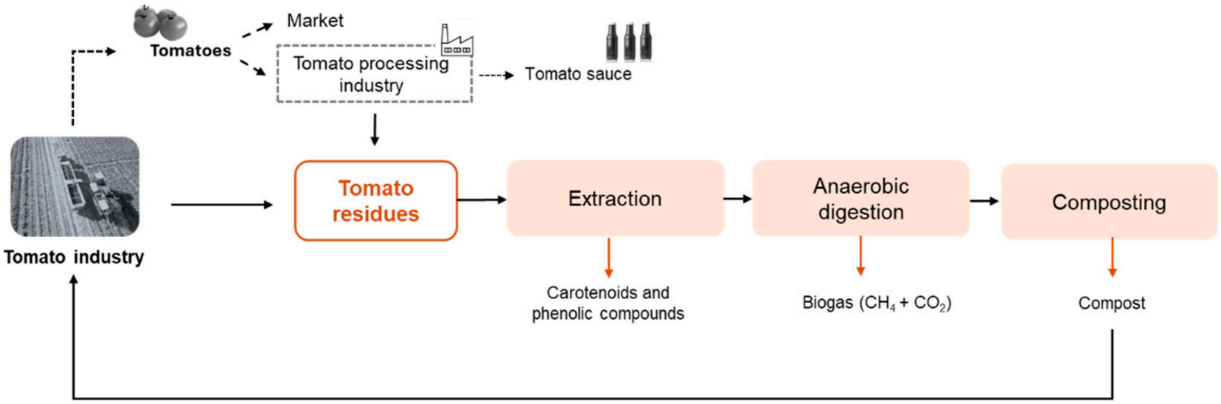


Figure 17. Cascaded valorization route of tomato residues through value-added extraction, anaerobic digestion, and composting [176]. Solid black arrows indicate the residue-processing sequence and the return of compost to the tomato industry. Dashed black arrows indicate tomato supply and product routes involving the fresh market and processing industry. Orange arrows indicate the outputs from each valorization stage: carotenoids and phenolic compounds, biogas, and compost [176].

Adjustable size reduction, field impurity removal, and segregated collection are potential equipment responses for matching feedstock quality to the selected utilization route.

Route selection should distinguish measured outcomes from synthesis and conditional estimates. Direct experimental endpoints include cross-crop cutting and grinding responses [166–170], rice pickup and chopping performance [172], preformed-rice-bale wrapping and storage [174], industrial-tomato soil-amendment responses [177], the 107-h tomato-residue compost heat balance [178], compost and vermicompost quality indices [179], and tomato-residue digestion under stated laboratory or pilot conditions [180,181]. Together, these endpoints provide components for a subsequent processing-tomato whole-chain assessment. Biomass-baling principles [173] and utilization reviews [175,176] provide complementary engineering and utilization context; cost comparisons remain dependent on their assumptions [171,172]. Net emissions require fuel, electricity, drying, film, storage, and treatment of CH4 and N2O, and soil effects to be compared against the same baseline with explicit displacement credits. Matched tomato field and logistics data are still needed to evaluate net energy, soil-compaction effects, and greenhouse-gas benefits. Table 7 links material properties to treatment requirements and the remaining measurement gaps.

Table 7. Vine-residue properties, treatment requirements, downstream uses, and measurement gaps. The indicators guide further assessment, with moisture basis, functional unit, baseline, and system boundary supporting consistent energy and cost comparisons.

Residue Property	Handling Implication	Treatment Requirement	Compatible Downstream Use	Evidence and Measurement Gap
High moisture	Adhesion, mass, storage instability	Manage drainage, storage time, and process moisture	Incorporation; formulated wet digestion or composting	Record moisture basis, storage losses, and drying demand to develop tomato-specific criteria
Long, fibrous, entangled vines	Wrapping and irregular feeding	Cutting, tearing, anti-wrapping feed	Incorporation; compost; densification	Cutting and grinding measurements [166–170]; match particle-size and energy denominators for tomato trials
Low bulk density	Large transport volume	Match collection, compression, and binding to destination	Centralized composting, digestion, energy	Baling principles [173] and measured rice wrapping [174] inform tomato density, rebound, and transport break-even trials
Soil and plastic	Wear and feedstock quality loss	Height control, separation, clean pickup	Clean compost/digestion/ feedstock routes	Report soil and plastic mass fractions, removal losses, wear, and destination limits
Mixed particle sizes	Uneven mixing, aeration, pumping, conversion	Route-specific size reduction and screening	Compost, digestion, thermochemical routes	Compost heat was assessed over 107 h [178]; batch and pilot digestion were tested [180,181]; field-grinding and whole-chain energy comparisons could extend assessment
Soluble organics and residual fruit	Composition, leachate, and biological-stability constraints	Prompt containment and mixing	Composting or formulated co-digestion	Measure dry-matter loss, product yield, storage duration, and CH_4/N_2O to assess net emissions

8. Summary and Outlook

8.1. Current Research Status

The 183 cited publications contribute complementary crop, material, component, and operational evidence, including 27 publications classified as direct processing-tomato evidence (Tables 1–3). Crop-establishment studies show how tillage and placement equipment interact under local field conditions [58,59], while tomato pickup tests quantify extraction and delivery at specified tray and moisture settings [49,53]. These findings support matching machinery to crop and agronomic conditions, with the measured endpoint defining the applicable contribution of each study.

Commercial processing-tomato harvesting studies identify losses and damaging contacts across the handling chain [2,6]. Their model-specific observations support coordinated attention to feeding, separation and transfer rather than optimization of an isolated component. The separation and cleaning comparisons show how excitation and material loading interact with quality and recovery; transferable crop studies add methods for examining these mechanisms. Existing evidence is consequently most informative for

selecting condition-specific operating ranges and identifying the measurements needed to extend them.

Tomato yield estimation [119,120], greenhouse fruit detection [122], symptom-recognition methods [112], and image-based quality prediction [124] have advanced distinct sensing and prediction tasks. Actuator-linked sorting prototypes add execution evidence, while quality-aware harvester feedback and cross-stage coordination remain promising integration directions. Table 8 distinguishes these functional contributions from their validation scopes, allowing recognition, decision support, and execution to inform system development without treating them as one maturity sequence.

Table 8. Functional roles and verification contexts for sensing, control, and cross-stage coordination; rows organize complementary functions and validation scopes.

Function or Verification Context	Required Demonstration	Evidence and Boundary	Supported Claim	Further Verification
Perception: offline recognition or online detection	Labels and independent splits; online delivery and timing logs	Tomato sensing [112,122,124] provides inputs for intervention trials	Recognition on tested data; timing logs support online detection assessment	External domains, failures, end-to-end delay
Prediction or state estimation; decision support	Prediction: independent test; decisions: rules, constraints and outcome tests	Yield prediction [119,120] provides a foundation for decision-outcome trials	Prediction within tested scope informs subsequent decision assessment	External prediction tests; separate decision trials against a baseline
Automatic execution	Command, actuator, achieved motion and timing	Sorter prototype [145]; limited test scope	Automatic action provides a basis for measured feedback trials	Missed actions, false rejection, load and safety
Closed-loop control	Measured response changes the next command	Whole-machine tomato quality feedback offers a further validation direction	Feedback for the measured variable under tested conditions	Disturbance response, delay, stability and safe fallback
Whole-machine field validation: test scope	Complete machine, baseline and field conditions	Component results inform subsequent whole-machine control trials	System outcome within documented test conditions	Replicated sites/seasons; output, quality, energy and cost
Cross-stage coordination: integration scope	Shared IDs, timed interfaces and joint constraints	Framework in Section 8.2 is proposed	Information linkage supports trials of coordinated closed-loop outcomes	Matched chain comparison, burdens and interface failures

8.2. Cross-Stage Coordination and Sustainability Implications

Figure 18 links agronomic management and machine operation through shared crop-state information while retaining a separate feedback path within each loop. In the proposed irrigation loop, soil-water, weather, and crop observations inform estimates of demand or stress; decisions on timing and amount drive pumps and valves; delivered flow and subsequent soil-water response update estimation and the next decision. Precision-irrigation and delivery studies contribute supporting methods [103–105], with the sprinkler-technology synthesis adding scheduling and controller concepts [107]. Image-based symptom recognition can guide inspection [112], with diagnostic confirmation and treatment thresholds supplying additional decision information. Plot- and time-linked records could relate

management and crop health to harvest readiness, providing context for later machine settings rather than a direct irrigation command to the harvester.

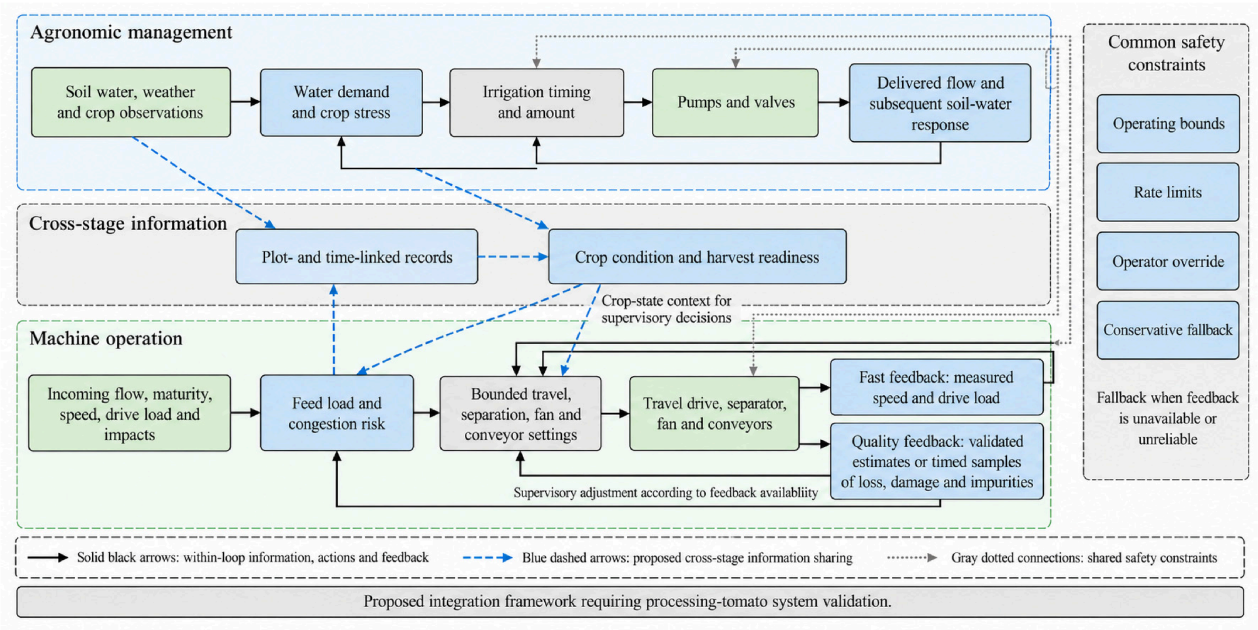


Figure 18. Proposed feedback loops linking agronomic management, crop monitoring and machine operation through cross-stage information sharing and common safety constraints. The integrated architecture requires system-level validation in processing-tomato production.

The proposed machine loop combines incoming flow, maturity, speed, drive load, and impact observations to estimate feed load and congestion risk. Bounded decisions then adjust travel, separator, fan, and conveyor drives. Grain-flow sensing contributes load-measurement methods [161], rice-kernel vision supplies a controlled quality-sampling example [162], and motor-driven maize seeding relates drive response to measured placement outcomes [163]. Together, these methods suggest crop-specific tests that connect measured load and quality with actuator commands and subsequent operating results. Measured speed and drive load can support fast updates, whereas loss, damage, and impurities require validated estimates or timed samples; their availability determines the supervisory adjustment interval. Common safety constraints apply to decisions and actuation in both loops, including operating bounds, rate limits, operator override, and conservative fallback. The framework identifies interfaces for integrated trials, with fixed-setting or operator-controlled baselines providing a practical comparison.

Cross-stage sustainability assessment can connect operation-specific water, input, labor, and loss measurements (Tables 6 and 7) through a common functional unit and a boundary covering marketable output, energy, logistics, and residue destination. The integrated architecture provides a framework for system-level processing-tomato trials.

8.3. Research Needs and Development Opportunities

Figure 19 combines the reported validation coverage with task-specific research priorities. Panel (a), drawn from Table 2, shows 93 publications reporting controlled or bench tests, 13 component field tests, 22 whole-machine field tests, and four commercial-operation records. These selected labels can overlap and include different crops and systems. Panel (b) distinguishes reported sensing, prediction, and sorting contributions from proposed quality-aware feedback and cross-stage coordination. Together with the descriptive appraisal in Table 3, the figure supports priorities organized by the available evidence, production relevance, and remaining deployment requirements.

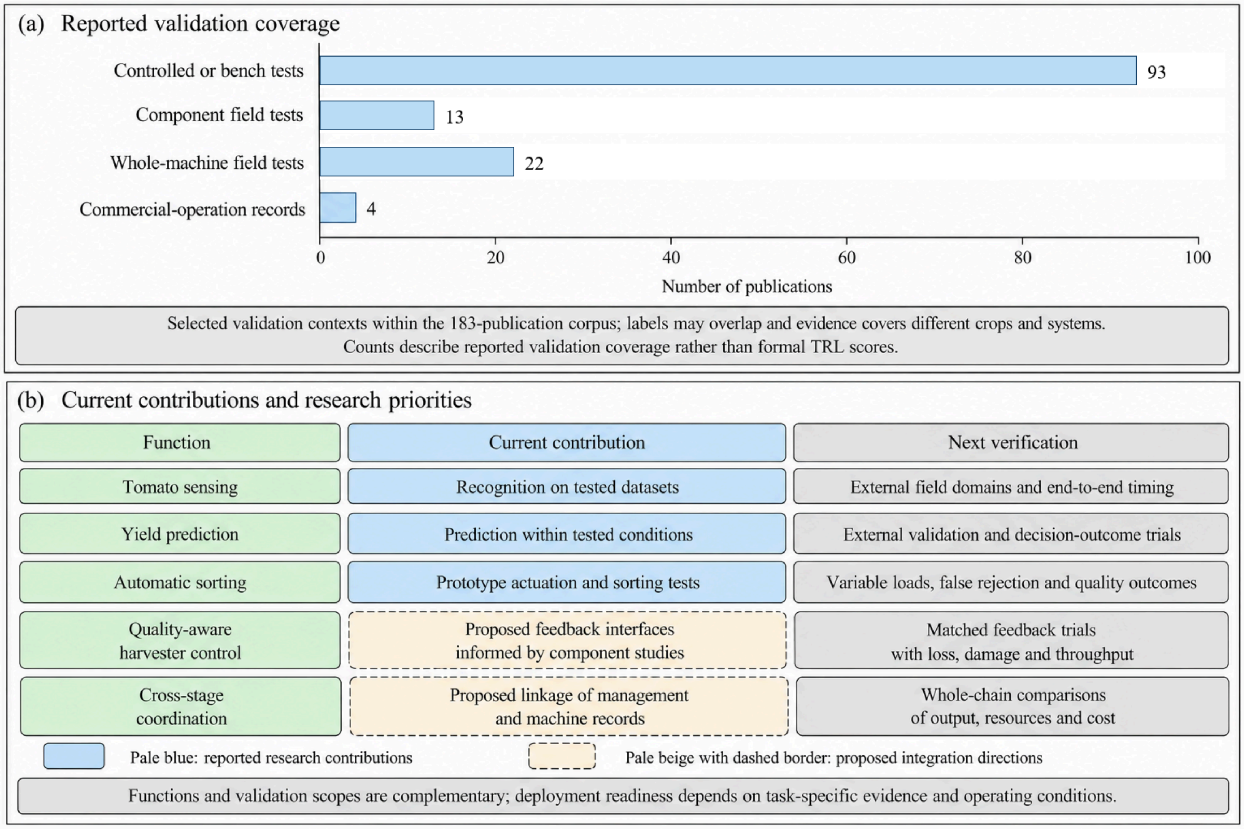


Figure 19. Reported validation contexts and research priorities for intelligent mechanization of processing-tomato production. Panel (**a**) summarizes selected contexts coded in Table 2; categories may overlap and cover different crops and systems. Counts indicate reported validation coverage rather than formal technology readiness levels. Panel (**b**) distinguishes reported functional contributions from proposed integration directions and identifies their corresponding verification priorities. Pale green cells identify the function column; pale blue cells indicate reported research contributions; gray cells identify next-verification priorities; and pale beige cells with dashed borders indicate proposed integration directions. These colors distinguish content categories and evidence status, not technology-readiness or quality rankings.

The immediate priority is to consolidate operating guidance for established machinery through paired crop–machine measurements and matched comparisons. Recording cultivar, maturity, material condition, machine configuration, and consistent outcome definitions would support operating maps that jointly describe recovery, damage, impurity content, and output. The harvesting comparisons identify interactions worth resolving experimentally, including excitation versus damage and feed loading versus cleaning performance. Adding elapsed-time energy and cost measurements to these trials would connect local adjustments with usable production benefits. Such work can build directly on existing commercial and component observations, with additional sites and seasons defining the range of applicability.

The next priority is to connect validated sensing and prediction with bounded intervention. Classification, detection, and regression require task-appropriate metrics, while external field domains test transfer beyond the original data. Validation should distinguish independent fruits, plants, or sequences from repeated images, preserve class information, and separate related observations before augmentation or preprocessing [183]. Existing greenhouse recognition [112,122] and tomato detector timing [149] provide starting points for field tests of occlusion, illumination, dust, and variable feed. Measuring the full acquisition-to-actuation delay, along with false rejections, missed actions, and operator

fallback, would establish whether computational gains improve intended operation. Table 8 links each function to the corresponding demonstration, including separate outcome trials for decision support and measured-response trials for feedback.

Longer-term development can evaluate quality-aware whole-machine control and agronomy–harvest coordination through synchronized records and shared operating constraints. Matched chain comparisons should track how changes redistribute energy, labor, loss, and costs among stages, using an explicit functional unit and system boundary. Sensitivity to yield, equipment utilization, energy supply, and residue destination would clarify where integration delivers net benefits. Exploratory interfaces can be developed alongside the earlier priorities, with deployment decisions guided by demonstrated output and quality gains and by calibration, maintenance and infrastructure requirements.

8.4. Limitations of This Review

This review has three principal limitations. First, literature identification was structured but non-systematic, using selected databases and publisher platforms, backward reference tracing, and relevance-based prioritization. The evidence map describes the 183 cited publications and their contributions, with potential differences from a comprehensive field-wide search. Broader systematic identification and harmonized effect estimation remain opportunities for subsequent work.

Second, variation in crop state, field conditions, machinery, operating settings, and indicator definitions favors comparisons within matched contexts. The descriptive appraisal identifies different levels of detail in replication, validation, and reproducibility; 11 season-and-location fields remain unresolved. Third, evidence from other tomato systems and crops contributes mechanisms and trial concepts, while processing-tomato validation can refine the relevant operating ranges. The 27 A/B publications include distinct crop, material, component, and operational endpoints, which are interpreted within their measured scope. Coordinated energy, cost, and life-cycle reporting would further strengthen sustainability synthesis. The evidence distribution and appraisal in Tables 1–3 complement the operation-specific comparisons in Tables 4–8.

8.5. Conclusions and Outlook

This review supports crop–machine coordination as a basis for mechanized processing-tomato production. Direct crop and harvesting studies show that suitable machinery and settings depend on plant and fruit condition, establishment geometry, and successive handling contacts. Commercial impact diagnosis supports model-specific damage reduction, while sensing, prediction, and sorting studies contribute distinct functions for further integration. Residue handling is most usefully selected according to the intended utilization route and its material requirements.

Development priorities follow the strength and scope of this evidence: first, refine established operations through comparable crop–machine measurements; next, test sensing-linked interventions and bounded feedback against practical baselines; and then extend verified operation-level functions to coordinated production-chain trials. Standardized outcome definitions support all three priorities. Sustainability assessment should retain marketable output and quality alongside energy, cost, and residue destination, so that demonstrated operation-specific benefits inform condition-specific system choices.

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