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Understanding Organizational Readiness for AI in Quality Control: A Case Study in Grape Leaf Processing through Stakeholder Interviews

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Abstract

This thesis examines the organizational readiness of a grape leaf processing company operating in China for the potential adoption of Artificial Intelligence (AI) tools in Quality Control (QC), with an emphasis on the receiving and initial inspection stage of raw materials. The study does not technically evaluate any specific AI system, but explores the organizational, technological and operational prerequisites that may facilitate or limit a future implementation of AI-supported QC. The research followed a qualitative single-case study approach and was based on six semi-structured interviews with information-rich participants from Management, Production and Quality Control, selected to capture different functional perspectives, company units and QC shifts. The data were analyzed through thematic analysis, with a combination of deductive coding, based on the conceptual framework, and inductive coding, based on the field data. The analytical framework linked the Technology–Organization–Environment (TOE) factors to the change commitment and change efficacy dimensions of organizational readiness.

The company already has a functioning QC system, with basic recording and traceability routines in place. Even so, incoming inspection still depends heavily on human judgement, experience-based assessment, and partly manual records. Participants saw AI as useful mainly where the current process is most exposed to pressure: fast acceptance, rejection, or classification of incoming loads. Its value was linked to more consistent decisions, better use of QC data, and stronger documentation, but not as an automatic replacement for human judgement. Acceptance of AI was therefore conditional. Any future solution would first need to prove that it can work under the actual receiving conditions of the company, fit the seasonal production environment, support staff rather than disrupt their work, and offer clear business value. Overall, the company appears willing to consider AI-supported QC, but its implementation capacity is not yet fully mature. A limited pilot in incoming inspection, combined with human oversight, clearer ownership, and better-structured QC data, is therefore the most realistic next step.

Keywords

Artificial Intelligence, Quality Control, Organizational Readiness, Grape Leaf Processing, TOE Framework, Change Efficacy

Λέξεις-κλειδιά

Τεχνητή Νοημοσύνη, Ποιοτικός Έλεγχος, Οργανωσιακή Ετοιμότητα, Επεξεργασία Αμπελόφυλλων, Τεχνολογία–Οργανισμός–Περιβάλλον, Ικανότητα Υλοποίησης Αλλαγής

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List of Abbreviations & Acronyms

AI: Artificial Intelligence

CNN: Convolutional Neural Network

CTE: Critical Tracking Event

FAIR: Findable, Accessible, Interoperable and Reusable

FAO: Food and Agriculture Organization of the United Nations

FDA: U.S. Food and Drug Administration

FT-NIR: Fourier Transform Near-Infrared

GDPR: General Data Protection Regulation

GS1: Global Standards 1

H: Hypothesis

HACCP: Hazard Analysis and Critical Control Points

HSI: Hyperspectral Imaging

IoT: Internet of Things

ISO: International Organization for Standardization

IT: Information Technology

KDE: Key Data Element

LC-MS: Liquid Chromatography–Mass Spectrometry

LR: Literature Review

ML: Machine Learning

NIR: Near-Infrared

NMR: Nuclear Magnetic Resonance

Obj: Objective

ORIC: Organizational Readiness for Implementing Change

QA: Quality Assurance

QC: Quality Control

QI: Quality Inspection

ROI: Return on Investment

RQ: Research Question

SMEs: Small and Medium-sized Enterprises

SORS: Spatially Offset Raman Spectroscopy

SQC: Statistical Quality Control

SRQR: Standards for Reporting Qualitative Research

TAM: Technology Acceptance Model

TOE: Technology–Organization–Environment framework

TPB: Theory of Planned Behavior

TQM: Total Quality Management

TSS: Total Soluble Solids

UTAUT: Unified Theory of Acceptance and Use of Technology

1 Chapter 1 - Introduction

1.1 Background and Context

1.1.1 Artificial intelligence and quality management in contemporary organizations

Quality management has developed from simple quality inspection (QI) to Total Quality Management (TQM) (Sütőová, Vykydal & Wawak, 2023, p. 27). The modern approach is holistic, focused on continuous improvement, customer satisfaction and employee participation (Navarro & Bayona, 2025, p. 82). Quality 4.0 extends this logic by linking total quality principles with digital and "smart" technologies, such as the Internet of Things, big data and artificial intelligence (Sütőová, Vykydal & Wawak, 2023, pp. 8, 27). In this context, AI is relevant because it influences how organizations design and implement quality management practices (Navarro & Bayona, 2025, p. 82).

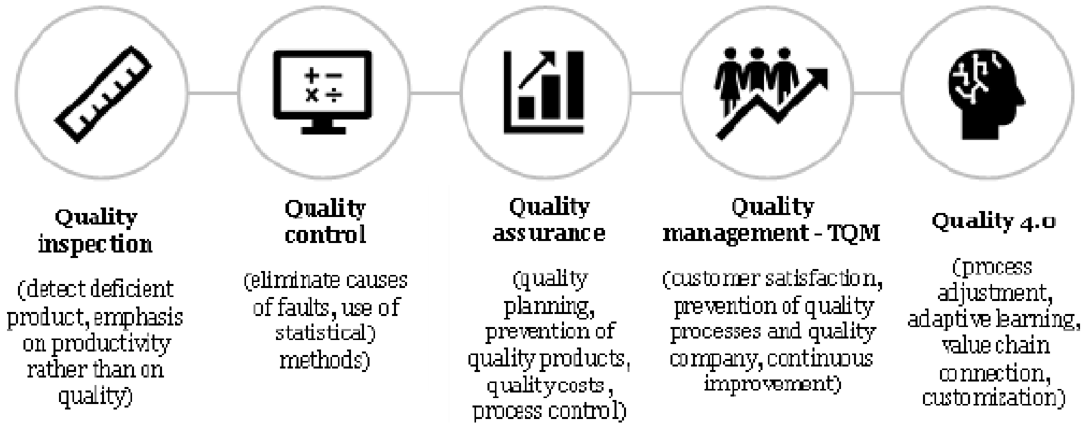

Figure 1.1 Evolution of quality management approaches
Note. From Introduction to Quality 4.0 (p. 27) by Sütőová et al. (2024).

1.1.2 AI applications in food quality control and agri-food supply chains

In agri-food, artificial intelligence connects Quality 4.0 with practical applications across the "farm-to-fork chain" (Liu et al., 2023, pp. 1–2; European Parliament, 2023, p. 15). In QC, machine learning and computer vision are relevant because they can make inspection faster, more repeatable and less dependent on destructive testing. They can support visual grading, defect detection, product classification, contamination checks and predictions related to shelf life, microorganism growth and process deviations within systems such as HACCP and ISO 22000 (Liakos et al., 2025, p. 2). For this thesis, the issue is whether such tools can fit the receiving and QC routines of a grape leaf processing company.

AI also supports decisions beyond factory inspection, where raw material quality, storage, transport and demand data need to be connected. Intelligent sorting, IoT-based monitoring and forecasting can reduce losses and improve traceability (Mengistu & Ashe, 2025, pp. 92–93; Palakurti, 2022, p. 57), while machine learning combined with blockchain or digital twins can follow product and information flows in real time (Liakos et al., 2025, p. 2). Its value therefore depends on use conditions: available data, staff able to interpret outputs, and coordination across supply-chain actors. For this reason, AI adoption in food supply chains is also an organizational readiness issue, not only a technology issue (Dora et al., 2022, p. 4621; European Parliament, 2023, pp. 15, 59, 64).

1.1.3 Organizational readiness as a critical factor for AI adoption in agri-food SMEs

The introduction of Artificial Intelligence (AI) tools in quality control is not only a technological upgrade; it is also an organizational change. Weiner (2009, p. 2) defines organizational readiness for change as a shared state in which members feel committed to change and confident in their collective ability to implement it.

In AI adoption studies, readiness refers to the organization's ability to use new technologies effectively (Issa, Jabbouri, & Palmer, 2022, p. 12). In SMEs, this depends on structures, processes, resources and people that can either support or limit adoption (Badghish & Soomro, 2024, pp. 4–6). In resource-constrained agri-food settings, readiness also requires standardized processes, basic information systems, ecosystem support, gradual adaptation, good data and digital skills (Arechavala-Vargas et al., 2025, pp. 45, 51; European Parliament, 2023, pp. 5, 59). For the company examined here, AI readiness therefore concerns management support, QC procedures, usable data, staff skills and willingness to test AI in daily QC work.

1.2 Research Motivation, Aim and Objectives

1.2.1 Practical motivation: challenges and opportunities of AI-enabled quality control in a grape-leaf processing company

In food companies, manual inspection, laboratory testing and batch sampling remain important parts of QC. However, these methods do not always support fast decisions at the point where raw material first enters the process, especially when delays, waste, rework or additional handling costs may already have been created (Liakos et al., 2025, p. 2; Abass, 2024, pp. 823–825). This is one reason why machine learning and related AI tools have become relevant for food QC: they can support faster, non-destructive checks, visual inspection, sorting and prediction of deviations linked to shelf life, microbial growth or process conditions (Liakos et al., 2025, pp. 2–3). Their value, however, depends on the existence of usable data, basic digital infrastructure and staff who can understand and apply the outputs in daily work (Abass, 2024, pp. 823–825; Mengistu & Ashe, 2025, pp. 92–93).

This issue is particularly relevant in fresh and leafy raw materials, because the product is naturally variable and sensitive to handling. Leaves may differ in size, shape, colour, surface condition and mechanical damage, and this variability can affect both processing and final product quality (Zhang et al., 2025, p. 26). In fresh produce, machine vision and machine learning are already used for sorting, grading, defect detection, foreign-body detection and packaging checks (Liakos et al., 2025, p. 7). AI can also contribute to food safety, traceability and loss reduction across the wider supply chain (Liu et al., 2023, p. 1; Monteiro & Barata, 2021, p. 2; Mengistu & Ashe, 2025, p. 92).

In the company examined in this study, these issues become more pressing because production is seasonal, daily receiving volumes are high, and incoming grape leaves vary in variety, size, colour, tenderness and damage. Current quality control relies heavily on manual sorting and the visual judgement of experienced operators. This allows fast practical decisions, but it also creates dependence on individual experience, staff availability and working conditions at the time of receiving. In a future scenario, AI-supported tools could help the company make leaf grading and acceptance decisions more consistent, document those decisions more clearly and link inspection results to specific batches. Therefore, for this company, organizational readiness for AI in QC is not an abstract issue. It is directly connected with operational pressure, cost, supplier-facing decisions and the strategic need for more consistent quality control.

1.2.2 Academic motivation: research gap on organizational readiness for AI in the agri-food sector

Beyond the practical motivation of this particular company, the study also addresses a research gap. The literature on AI in the agri-food sector has grown, but many studies still focus mainly on efficiency, productivity and profitability, for example through supply chain optimization and risk management (Trabelsi et al., 2023, p. 488). The same review notes that the human-centric and "soft" aspects of AI need more attention, suggesting that these dimensions remain underdeveloped (Trabelsi et al., 2023, p. 488). Monteiro and Barata (2021) also show that AI in the extended agri-food supply chain is still in a formative phase, with further research needed in areas such as storage, distribution, retail, consumers and circular flows (pp. 3027–3028). Their analysis also points to the need for flexibility, integration between business partners, coordinated planning and collaboration, which are organizational issues as much as technological ones.

Research on how SMEs and AgriTech firms prepare for AI adoption at the organizational level remains limited. Issa, Jabbouri, and Palmer (2022, p. 2) argue that AI and the AgriTech sector have their own characteristics, so existing technology adoption and readiness theories cannot always be applied without adjustment. Arechavala-Vargas et al. (2025, p. 42) similarly show that studies on SMEs in emerging economies often focus on traditional digital technologies rather than AI. As a result, there is still limited understanding of how these firms prepare for AI adoption in practice. Badghish and Soomro (2024, p. 2) also stress the need to examine the different, and especially qualitative, factors that influence AI adoption in SMEs.

At the policy level, the European Parliament study on AI in agri-food recognizes that, beyond technical benefits, questions remain about benefits and risks, AI governance, and the education and training needed to support users (European Parliament, 2023, pp. 3–4). However, these discussions do not examine in detail the internal organizational conditions of food businesses, such as change culture, governance structures, quality processes and staff skills.

The gap is therefore organizational rather than purely technical. Existing studies describe many AI applications in the agri-food chain, but say less about how smaller agri-food firms prepare internally for AI adoption, especially when AI is linked to quality control rather than general digital transformation. This thesis addresses that gap by examining AI readiness in a grape-leaf processing company, with a specific focus on QC and incoming inspection.

1.2.3 Research aim and specific objectives

Taking into account the practical and academic motivation presented in the previous subsections, this subsection formulates the overall research purpose and specific objectives of the study. In the methodological literature, the purpose briefly captures what the research seeks to achieve, while the specific objectives specify this purpose in clear, research-implementable steps (Abdulai & Owusu-Ansah, 2014, p. 6; Doody & Bailey, 2016, p. 19).

The aim of this thesis is to examine how ready a grape-leaf processing company is to adopt AI tools in quality control, based on the views and experience of key people involved in management, production and QC.

In line with the above purpose, the work is structured around the following specific research objectives:

1. To describe the existing quality control system and the current use of data and digital tools in the grape leaf processing company under consideration.
2. To investigate how executives and other key members of the organization perceive the challenges and opportunities from the integration of artificial intelligence tools in grape leaf quality control.
3. To analyze which organizational characteristics (structures, processes, resources, skills, culture of change) enhance or limit the company's readiness to adopt artificial intelligence in quality control.
4. To synthesize - based on the empirical findings - proposals for the gradual integration of artificial intelligence tools into the company's quality management system, taking into account the specificities of both agri-food companies and the specific company.

1.2.4 Research questions

Based on the research aim and specific objectives presented in subsection 1.2.3, this section formulates the research questions of the study. In the methodological literature, research questions are considered a central element of research design, as they determine exactly what will be investigated and influence the choices regarding data, sample and analysis methods (Doody & Bailey, 2016, p. 19). Research objectives usually guide the formulation of a central research question and individual secondary questions, which are presented in close connection with each other (Van der Waldt, 2025, p. 3).

In this context, the central research question of this thesis is:

- How is the organizational readiness of a grape leaf processing company shaped for the adoption of artificial intelligence tools in quality control?

This central question is further refined into the following secondary research questions, which correspond to the specific research objectives of subsection 1.2.3:

- How is quality control currently organized in the grape leaf processing company under consideration and what is the role of data and digital tools in its operation?
- How do executives and other key members of the organization perceive the opportunities and challenges from the integration of artificial intelligence tools in grape leaf quality control?
- Which organizational factors – such as structures, processes, resources, skills and culture of change – seem to enhance or limit the company's readiness to adopt artificial intelligence in quality control?
- Based on the empirical findings, in what ways can the company gradually enhance its organizational readiness and integrate artificial intelligence tools into the quality management system (e.g., HACCP, ISO 22000)?

The above questions structure the collection and analysis of data in the empirical part of the work and are directly linked to the discussion of the results and the conclusions of the following chapters. To address these questions, the study adopts a qualitative single-case study design focusing on a grape leaf processing company, with data collected primarily through semi-structured interviews with key organizational stakeholders. The research methodology is presented in detail in Chapter 4.

1.3 Scope and Delimitations of the Study

In this thesis, the scope defines the boundaries within which organizational readiness for the adoption of AI tools in quality control is examined. As Simon and Goes (2013, p. 1) note, scope concerns the parameters within which a study moves and what is included in its field of inquiry. In the present case, the analysis focuses on a Greek grape leaf processing company operating in China, and specifically on how management, production and QC actors perceive readiness for possible AI use in quality control. The study is limited to fresh grape leaf QC during the processing period from May to August, with emphasis on receiving and initial inspection.

The delimitations reflect deliberate research design choices, especially the single-case qualitative design, the selected participant groups, the theoretical framework and the focus on QC rather than on the full business operation. Delimitations are understood as boundaries created by the researcher's choices rather than by external constraints (Simon & Goes, 2013, p. 3; Theofanidis & Fountouki, 2019, p. 157). For this reason, the study uses key informants from Management, Production and QC, but does not include line workers, suppliers or customers. It also does not evaluate specific AI systems technically or measure financial outcomes quantitatively.

These boundaries also affect how the findings should be read. The single-company and season-specific focus means that the results are not statistically generalizable to all agri-food SMEs. They can, however, support an in-depth understanding of one case and allow analytical discussion in relation to the relevant theory. This is consistent with the need to make visible what is included and excluded from the research project (Coker, 2022, p. 143). The main limitations, including single-case design, time constraints and retrospective interview accounts, are discussed further in Chapter 4 (Simon & Goes, 2013, p. 1; Theofanidis & Fountouki, 2019, p. 156).

1.4 Structure of the Dissertation

This dissertation is structured in seven chapters:

- **Chapter 1 (Introduction)** presents the background, motivation, research aim, research questions, methodological overview, scope and delimitations.

- **Chapter 2 (Literature Review)** reviews artificial intelligence in food quality control, the agri-food supply chain and organizational readiness for AI adoption in SMEs.
- **Chapter 3 (Conceptual Framework & Research Hypotheses)** synthesizes the literature into a conceptual framework and formulates the research hypotheses examined in the empirical part of the study.
- **Chapter 4 (Research Methodology)** presents the qualitative case study design, sampling, semi-structured interviews, thematic analysis and trustworthiness measures.
- **Chapter 5 (Data Analysis)** presents the empirical findings, organized into main themes and sub-themes with indicative interview excerpts.
- **Chapter 6 (Discussion & Interpretation of the Results)** discusses the findings in relation to the conceptual framework and relevant literature.
- **Chapter 7 (Summary & Conclusions)** summarizes the conclusions, limitations, future research directions and practical recommendations for AI in quality control.

2 Chapter 2 - Literature Review

2.1 Chapter introduction

Chapter 2 constitutes a systematically structured review of the international literature that supports the objective of this thesis: understanding organizational readiness for the adoption of Artificial Intelligence applications in quality control in agri-food processing, with a focus on the raw material receipt/inspection stage. In this way, the chapter connects the framework and research questions of Chapter 1 with the conceptual elements required to formulate an analytical framework in Chapter 3.

The choice of a systematic review is made to reduce weaknesses that often characterize purely narrative approaches (e.g. incomplete coverage and increased risk of bias). In this context, the systematic search is based on predefined terms/keywords and a clearly defined search strategy, so that the collection of literature is auditable and consistent (Tranfield, Denyer, & Smart, 2003, pp. 207, 213). At the same time, emphasis is placed on transparency regarding the rationale, steps and results of the review (Page et al., 2021a, p. 1). Subsection 2.2 briefly describes the databases, search terms, inclusion/exclusion criteria and screening steps.

The presentation is organized conceptually, so that a synthesis emerges around key concepts (and not a listing of articles by author) (Webster & Watson, 2002, pp. xv–xvi). The chapter progresses from the Quality 4.0 framework and the role of AI (2.3) to AI applications in food quality control (2.4) and specifically in receiving/inspection (2.5), before examining data/infrastructure (2.6) and adoption–readiness theories (2.7–2.8). Finally, it concludes with a synthesis (2.9) and documented research gap (2.10), as a direct bridge to Chapter 3.

2.2 Systematic search approach

The literature review in Chapter 2 follows a structured approach designed to reduce limitations often associated with narrative reviews, such as selective coverage and increased risk of bias (Tranfield, Denyer, & Smart, 2003, p. 207).

The identification of the literature was based on a structured search with defined thematic axes and corresponding terms (AI/ML/computer vision, quality control/inspection/sorting, agri-food/food processing/supply chain, as well as adoption/readiness/SMEs where required), so that the collection of sources follows a consistent and auditable logic (Tranfield et al., 2003, p. 213). Furthermore, in order not to limit the coverage only to the results of the keywords, backward/forward searching was utilized, i.e. checking the bibliography of key articles and identifying newer works that cite them (Webster & Watson, 2002, p. xvi).

The search was carried out in the main bibliographic databases Scopus, Web of Science and IEEE Xplore, while Google Scholar and open platforms/indices (e.g. DOAJ, CORE, BASE, OpenAlex) were used in addition, mainly to identify available full-text publications.

The selection of studies was based on basic inclusion/exclusion criteria (thematic relevance, type/research documentation, ability to evaluate the full text where required) and followed a multi-stage process: initial title/abstract screening and then full-text evaluation when the study could not be safely excluded at the first stage (Kitchenham & Charters, 2007, pp. 18–19). The above logic is consistent with the principle that a systematic review should, to the extent possible, be transparent and reproducible in terms of its steps (Kitchenham & Charters, 2007, p. 16).

2.3 Quality management → Quality 4.0 → AI

Quality management did not take its current form at once. Earlier approaches focused mainly on inspection and control, while later approaches gave more attention to quality assurance and the broader logic of Total Quality Management. Sütőová et al. (2024, p. 26) describe this development through the sequence "quality inspection (QI) → statistical quality control (SQC) → quality assurance (QA) → total quality management (TQM)". This sequence is useful here because it shows how quality moved from checking defects towards more systematic control and improvement of processes.

Quality 4.0 continues this development, but places quality management inside the wider shift towards digital production and Industry 4.0. Radziwill (2018, p. 1) connects Quality 4.0 with the pursuit of performance excellence under disruptive digital change. In practice, this means that quality work is increasingly linked with digital systems, operational data and real-time information. Machine learning is relevant here because it can process large volumes of data and support faster process decisions. Carvalho et al. (2021, p. 342) note that information and communication technologies make it possible to integrate quality management into technological processes, while Efimova and Briš (2021, p. 40) link data analytics and AI with the collection, storage and processing of big data for more effective process management. This background leads to the next section, where AI applications in food quality control are discussed together with the organizational conditions needed for their adoption.

2.4 Artificial Intelligence in Food Quality Control: applications of Computer Vision, ML and spectroscopy/HSI

Food QC is increasingly linked to digital inspection and prediction tools, partly because food production involves multiple stages, stricter compliance requirements and higher traceability demands. Liakos et al. (2025, p. 1) show that recent ML applications cover visual defect detection, predictive QC, HSI, sensor fusion, explainable AI and practical implementation challenges such as data availability, integration with existing systems, regulatory compliance and scaling. For this thesis, the important point is narrower: these tools are relevant only if they can support practical QC decisions under the time pressure and variability of raw-material receiving.

At the level of visual quality control, computer vision/machine vision systems function as a digital "extension" of human vision for the evaluation of external characteristics (shape, color, surface, dimensions). Their basic logic is described as a combination of (a) image acquisition through appropriate equipment and (b) image processing/analysis, in order to extract indicators that lead to classification or rejection/acceptance decision (Xiao et al., 2022, p. 2).

In practice, the analysis flow is organized from low-level steps (acquisition & pre-processing for noise/illumination correction), to mid-level steps (segmentation/description) and to high-level steps (recognition/interpretation), which constitute the technical background of applications such as foreign body detection, defect identification, calibration and grading (Xiao et al., 2022, p. 4). The typical flow of a machine vision system and the role of deep learning are summarized in Figure 2.4.1 (Xiao et al., 2022, Figure 1)

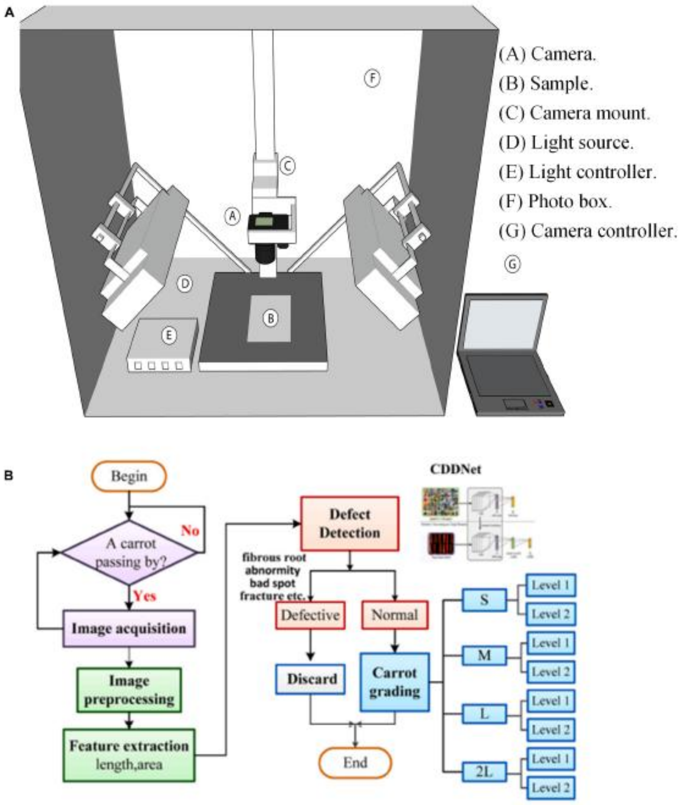

Figure 2.1 Computer technology applied to food engineering: (A) Computer vision systems; (B) overall flowchart of deep learning.
Note. Reproduced from Xiao, et al., (2022)

The integration of deep learning (especially CNN) has significantly improved the accuracy of visual recognition tasks, because the algorithms "learn" features directly from image data, reducing the need for manual feature extraction. However, the same source highlights operational limitations: training requires a large volume of images, high computing power and training time, while real-world line conditions (e.g. low light, humidity, noise) can introduce errors if the acquisition conditions and equipment are not controlled (Xiao et al., 2022, p. 5). Therefore, in food quality control, the effectiveness of computer vision solutions is not only a matter of algorithms, but also of standardizing the inspection environment (illumination, camera stability, field of view clarity) and data quality.

Beyond external features, a significant part of quality and safety is related to "invisible" parameters (chemical composition, moisture, maturation, spoilage). This is where spectroscopy comes in, and in particular hyperspectral imaging (HSI), which is described as a non-destructive method that provides both spatial and spectral information. In the review by Nikzadfar et al. (2024), HSI is presented as a tool that can detect contaminants/adulterations and quality characteristics (e.g., moisture, maturation, microbial spoilage) through spectral "signatures" across a wide range of wavelengths, with speed and accuracy (Nikzadfar et al., 2024, p. 1). The basic stages of hyperspectral data processing and decision making are depicted in Figure 2.4.2 (Huang et al., 2014, Figure 5).

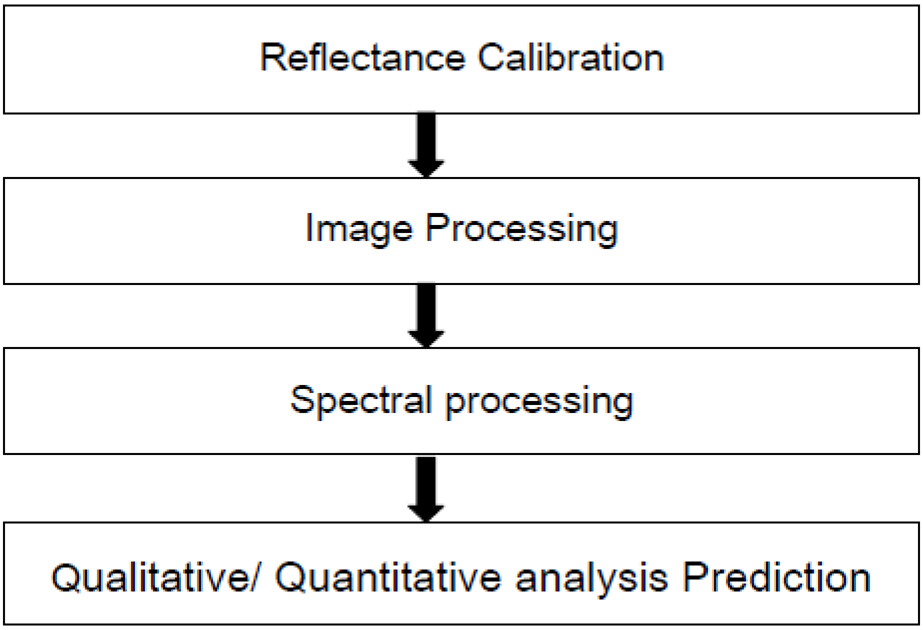

Figure 2.2 Flow diagram of hyperspectral data analysis process.
Note. Reproduced from Huang, et al., (2014)

In addition, the review by Huang et al. (2014) documents HSI as a promising technique for rapid, non-invasive food analysis, supporting applications in both quality and safety (Huang et al., 2014, pp. 7248, 7269). In this context, ML acts as a "bridge" that transforms high-dimensional spectral information into operational QC decisions (e.g. batch classification, deviation detection).

Finally, portable optical/infrared spectroscopy techniques are directly linked to the need for rapid evaluation of raw materials, as they aim to measure/estimate biochemical content in practical field/line modes. For example, Ricci et al. (2024) frame portable optical spectroscopy as an approach for quantitative assessment of specific quality indicators (e.g. protein in seeds, degree of ripeness in fruits) (Ricci et al., 2024, p. 1).

For incoming inspection, these technologies matter for different reasons. Computer vision can support checks of visible leaf characteristics; ML and deep learning can strengthen pattern recognition and classification; and spectroscopy or HSI can add information that is not visible to the eye. The next section therefore focuses on how such tools could operate at the receiving stage, where speed, stable inspection conditions and decision reliability are critical.

2.5 Artificial Intelligence at the raw material reception / incoming inspection stage: automated inspection, classification and batch acceptance decisions

The raw material receiving/incoming inspection stage acts as a critical decision point, because it is here that the decision is made whether a batch will be accepted, downgraded to another use, or rejected, with direct implications for quality, cost, and production flow. In the ML literature in food quality control, the receiving "gateway" is viewed as a typical high-speed node where: (a) rapid quality assessment without product destruction, (b) automated visual inspection/sorting, (c) the ability to predict or prevent deviations (e.g. shelf-life/microbial growth), and (d) the combination of heterogeneous data (image/spectrum/sensors) into a single quality profile are required. (Liakos et al., 2025, p. 2)

2.5.1 Automated Visual Inspection and Classification (Computer Vision + ML)

The main contribution of computer vision to acceptance is that it transforms a traditionally subjective process (operator visual judgment) into a measurable, repeatable inspection. Furthermore, recent literature shows that the transition to deep learning, and especially convolutional neural networks (CNNs), enhances food classification from images (Xiao et al., 2022, p. 4). Classic works on machine vision for agricultural/food products describe that the technology is widely used for defect detection, quality grading, and classification/categorization of products based on external characteristics (Patel et al., 2012, p. 124)

To be applicable at the receiving "door", computer vision is viewed as an integrated system (illumination–camera–capture–computing–software), not as a single algorithm. This systemic perspective is important in receiving, because the stability of the illumination, the acquisition geometry, and the collection speed directly affect the consistency of the classification (Patel et al., 2012, p. 125). The basic architecture of a computer vision system is summarized in Figure 2.5.1.

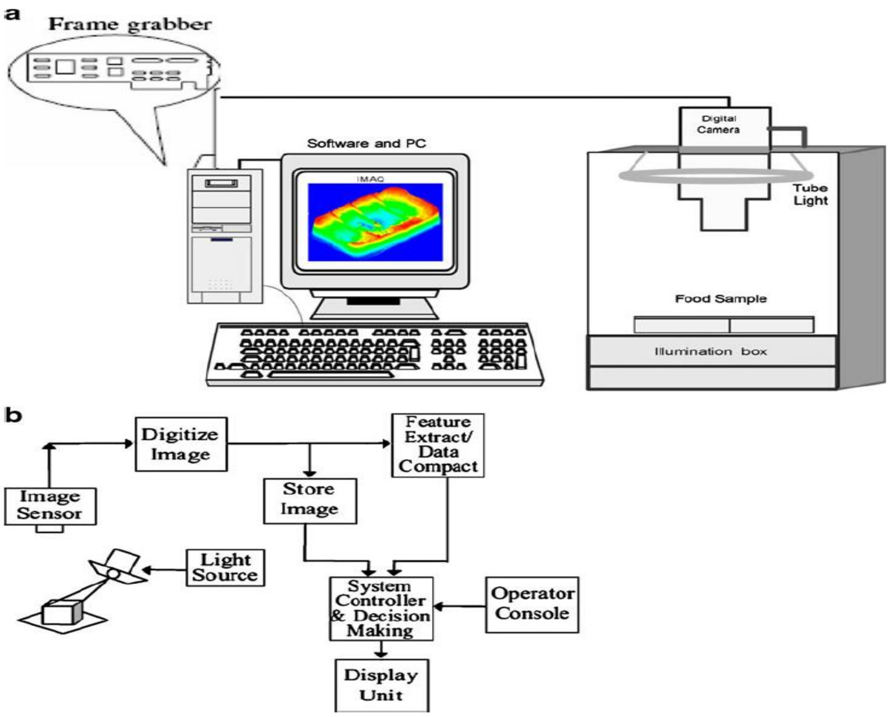

Figure 2.3 Basic components of a computer vision system for inspection/classification.
Note. Adapted from Patel, Kar, Jha, & Khan (2011, Fig. 1)

2.5.2 From piece-level classification to batch management (grading → batch decision)

At the quality management level, the aim is not only to classify "piece-by-piece", but to convert the results into batch indicators/criteria (e.g. defective rate, category distribution, uniformity). Indicatively, applications in fresh fruits and vegetables refer to the integration of multispectral/visible+NIR information in automatic sorting machines, as part of industrial inspection devices. (Saldaña et al., 2013, p. 258)

In parallel, in modern ML frameworks for QC, automated visual inspection is explicitly linked to grading/specification and to a high-throughput operation, so that it is realistic in high-volume incoming flows. (Liakos et al., 2025, p. 2)

2.5.3 Spectral techniques and HSI for "non-visible" or early deviations

When appearance is not enough (e.g., composition, early deterioration), the literature presents hyperspectral imaging (HSI) as a technology that combines spectral information (material/composition) with spatial signal (image). In a review of the field, HSI is described as

a rapidly developing, non-destructive and "real-time" approach for quality/safety assessment, precisely because it can provide both spatial and spectral information about the object. (Huang et al., 2014, p. 7248)

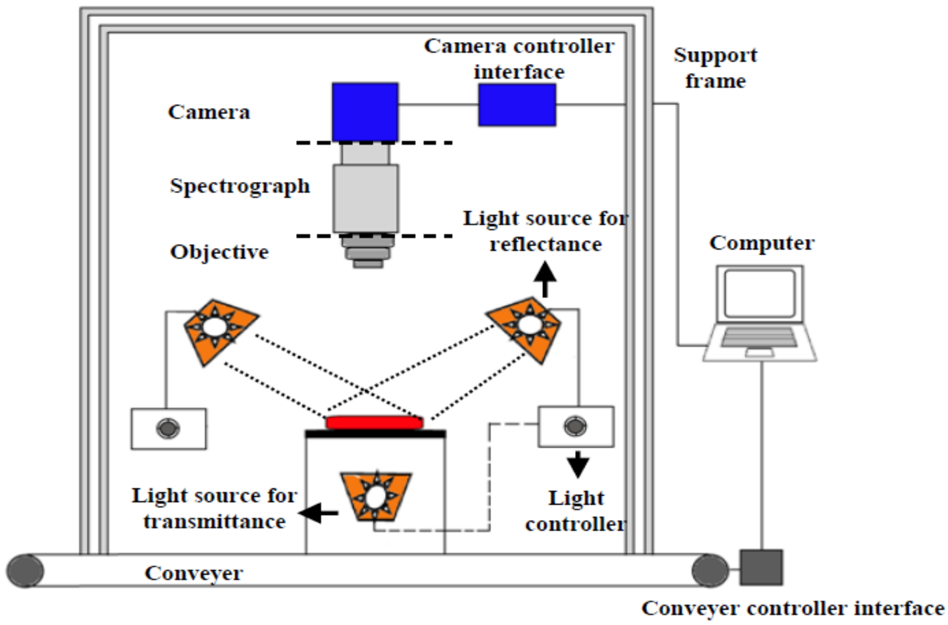

Figure 2.4 Layout/components of a hyperspectral imaging system.
Note. Adapted from Huang, et al., (2014, Figure 2)

In addition to the "theoretical" advantage, there are also examples of online/industrial logic: online HSI application for classification/sorting, aiming for high-throughput screening in an industrial environment, the performance of which depends on application conditions. (Faqeerzada et al., 2020, p. 1)

2.5.4 Portable / miniaturized equipment for screening at reception (handheld / portable spectroscopy)

In practice, receiving favors lower-cost and rapid-implementation solutions. This is why the literature emphasizes the transition from "lab" to "on-site" with miniaturized/handheld spectroscopy (especially NIR), which reshapes the scope of application because it allows analysis at the point of control, with particular benefits for the agri-food sector. (Beć et al., 2022, p. 2)

In more targeted applications, portable NIR spectroscopy is presented as a fast alternative to destructive laboratory techniques for the evaluation of biochemical indicators of raw materials (e.g. protein in seeds, TSS/"ripeness grade" in fruits), while it is explicitly proposed as a "first selection" tool upon arrival/receipt. (Ricci et al., 2024, pp. 1, 11)

In the same vein, reviews of handheld devices in food authenticity/integrity note that miniaturization has enabled the use of analytical devices outside the laboratory, including portable/handheld solutions, even integration into smartphones, while listing as "promising" categories of technologies (e.g. optical/imaging sensors, NMR, sensor arrays) in lightweight/portable forms. (Müller-Maatsch et al., 2021, pp. 1–2)

2.5.5 Data fusion and complementary measurements for more reliable incoming decisions

Finally, for more "difficult" cases (heterogeneous raw material, defects not fully captured by one method), the literature highlights the combination of methods and data fusion as a way to improve classification, because different sensors can provide complementary information. In a pilot study for FT-NIR and SORS in raw material defect detection, it is explicitly stated that the combination of the two in low-level data fusion improved classification models and that the analysis with FT-NIR/SORS has the potential to detect "abnormal samples" in incoming goods inspections. (Lösel et al., 2024, p. 486)

At the same time, it is emphasized that high-precision techniques (e.g. LC-MS/NMR) have limited practical use in incoming inspections due to sample preparation, cost, and the need for specialized personnel—an element that reinforces the logic of "fast screening on receipt" with portable/spectral solutions and ML models. (Lösel et al., 2024, p. 491)

At the receiving stage, AI would most realistically develop step by step: first through fast visual inspection or sorting, then through spectral or HSI methods when deeper quality information is needed, and later through portable screening tools and data fusion. The practical objective is not full automation from the beginning, but a more consistent and better documented batch acceptance decision.

2.6 Data and digital infrastructure in the agri-food chain: IoT, data quality and traceability

The effectiveness of the AI applications described in 2.4–2.5 (e.g. computer vision/ML and sensors/spectral techniques in the acquisition) depends to a large extent on the existence of a functional digital data infrastructure: mechanisms for collecting, storing, connecting and disseminating data in a way that enables reliable decisions and documentation. At the level of data governance, the FAIR principles summarize the minimum requirements for (meta)data to be Findable, Accessible, Interoperable and Reusable, i.e. they act as high-level guiding principles for how data/metadata are organized and "housed", even before a technology or platform is selected (Wilkinson et al., 2016, p. 6). The individual principles are summarized in Figure 2.6.1.

Box 2 | The FAIR Guiding Principles

To be Findable:
F1. (meta)data are assigned a globally unique and persistent identifier
F2. data are described with rich metadata (defined by R1 below)
F3. metadata clearly and explicitly include the identifier of the data it describes
F4. (meta)data are registered or indexed in a searchable resource

To be Accessible:
A1. (meta)data are retrievable by their identifier using a standardized communications protocol
A1.1 the protocol is open, free, and universally implementable
A1.2 the protocol allows for an authentication and authorization procedure, where necessary
A2. metadata are accessible, even when the data are no longer available

To be Interoperable:
I1. (meta)data use a formal, accessible, shared, and broadly applicable language for knowledge representation.
I2. (meta)data use vocabularies that follow FAIR principles
I3. (meta)data include qualified references to other (meta)data

To be Reusable:
R1. meta(data) are richly described with a plurality of accurate and relevant attributes
R1.1. (meta)data are released with a clear and accessible data usage license
R1.2. (meta)data are associated with detailed provenance
R1.3. (meta)data meet domain-relevant community standards

Figure 2.5 The FAIR Guiding Principles (Findable, Accessible, Interoperable, Reusable).
Note. From Wilkinson et al. (2016), Box 2

Furthermore, the principle of "machine-actionable" usage means that not only humans but also systems can locate, read, connect and reuse data/metadata in an automated manner (Wilkinson et al., 2016, p. 5).

The Internet of Things (IoT) is understood as the technological paradigm that connects "everyday" physical objects/devices to the internet, in order to collect and transmit data for operational exploitation (Mansouri et al., 2021, p. 1). In the agri-food chain, the IoT is a key "channel" for the production of field/line data (e.g. temperature, humidity, time/location, transport-storage events), especially for perishable products.

At a more operational level, the literature on IoT-based temperature monitoring in fresh produce chains emphasizes indicators such as transmission reliability, temperature/location accuracy, and sustainability characteristics, while also examining economic impacts with the aim of reducing discards and losses (Lamberty & Kreyenschmidt, 2025a, p. 1; Lamberty & Kreyenschmidt, 2025b, p. 1). Figure 2.6.2 shows how IoT data (devices/sensors) acquire the form of event data and are linked to an operational context, so that they can be used in traceability systems.

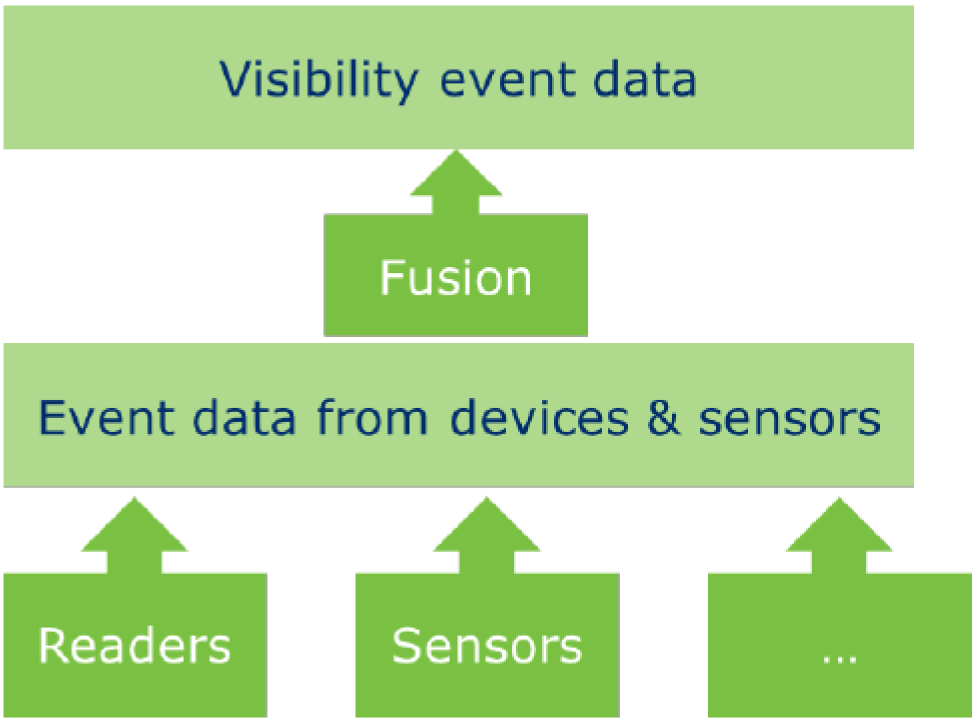

Figure 2.6 Visibility event data from devices & sensors and the Internet of Things (IoT).
Note. From GS1 (2017), p. 37, Figure 4-4

Traceability acts as the structural backbone that links data to products, batches and processes. At the definitional level, Codex describes traceability as the ability to track the movement of a food through defined stages of production, processing and distribution (Codex Alimentarius Commission, 2006, p. 1). In addition, FAO approaches it as an operational process that allows trading partners to follow products from the field to the retail/catering (FAO, 2017, p. 2).

For the needs of a chain that runs at high speed (such as raw material receipt), traceability is not just compliance: it is the mechanism that allows measurements/decisions to be consistently linked to specific batches and to support the management of deviations.

To be functional in practice, traceability requires standardization in identification and event data. GS1 defines traceability as the ability to trace the history/application/location of an object and links the practical application with traceability to direct suppliers and direct recipients (GS1, 2017, pp. 6, 16).

Finally, even with sensors and standards, the "critical point" remains the quality of the data: if it is incomplete, inconsistent or not comparable, both traceability and AI models are undermined (especially when linking inspection results to batches and historical events). The literature summarizes key dimensions of data quality (e.g., accuracy, timeliness, completeness, reliability) and suggests a categorization specifically for IoT environments with multiple dimensions and quality issues (Mansouri et al., 2021, pp. 2, 8).

In terms of readiness, this translates into a need for data management processes/roles (data ownership, recording rules, controls, "naming" of batches/events), so that technology (IoT/AI) can tap into reliable information and not "noisy" recording.

2.7 Technology Adoption and Organizational Readiness Theories

Sections 2.4–2.6 focused on technologies and data requirements; however, their successful implementation in practice is linked to issues of acceptance and organizational integration, which are theoretically examined in this section. The literature on innovations in organizations emphasizes that success is not limited to individual use, but is linked to the organizational assimilation of complex solutions (Greenhalgh et al., 2004, p. 601). Furthermore, it conceptually distinguishes diffusion as passive dissemination from dissemination as an actively planned dissemination effort, a distinction useful in describing how a technology "moves" within an organization (Greenhalgh et al., 2004, p. 582).

2.7.1 Individual level: intention and user acceptance (TPB, TAM/UTAUT)

At the individual level, the Theory of Planned Behavior (TPB) posits intention as a central mechanism that encapsulates the "motivation" to perform a behavior (Ajzen, 1991, p. 181). In the context of this thesis, the TPB helps to explain why executives/operators may show different willingness to move from empirical judgments to more standardized use of digital.

In the field of information systems, the Technology Acceptance Model (TAM) is founded on the concepts of perceived usefulness and perceived ease of use, which function as key determinants of acceptance. In this regard, "usefulness" is defined as the extent to which an individual believes that using a system improves their work performance, while "ease" is defined as the extent to which use is effort-free (Davis, 1989, pp. 319-320). For AI applications in quality control/receiving, the two concepts translate practically into (a) perceived benefit in speed/consistency of decisions and (b) ease of integration into the workflow without "friction" or excessive burden.

UTAUT is proposed as a unifying approach that "brings together" elements from multiple adoption/acceptance models, aiming for a more comprehensive explanation of technology use (Venkatesh et al., 2003, p. 425) and is explicitly positioned as a synthesis of previous lines (e.g. TAM, TPB) (Venkatesh et al., 2003, p. 425). In its empirical application, it focuses on determinants associated with acceptance and usage behavior (Venkatesh et al., 2003, p. 447). For the present research, UTAUT is useful as a "bridge" between individual perceptions (e.g., expected benefit/burden) and the organizational context that shapes them (e.g., support, training, resource availability).

2.7.2 Organizational level: the Technology–Organization–Environment (TOE) framework

At the firm level, the Technology–Organization–Environment (TOE) framework is used to examine adoption through three areas: technology, organization and environment (Baker, 2012, p. 2). The organizational area includes firm characteristics and resources, such as internal communication, links between employees and company size (Baker, 2012, p. 3). In the present study, this framework helps to keep the analysis of the grape leaf processing plant focused on practical questions: what data and infrastructure are available, how roles and processes support their use, and how customers, suppliers or rules affect quality control.

2.7.3 Readiness for change as a specific form of organizational interpretation

Readiness for change is also needed in this study because AI in quality control would not simply add a new tool. It could affect routines, responsibilities and decision rules, especially during incoming inspection. Weiner's theory is useful here because it defines organizational readiness as a shared psychological state: members are committed to the change and also believe that they can implement it together. This distinction is captured through change commitment and change efficacy (Weiner, 2009, p. 1). In the present case, it helps to separate two different issues. Employees and managers may see AI as valuable for QC, but this does not automatically mean that they feel able to implement it, especially if there are doubts about data, skills, resources or the practical conditions of the receiving process.

2.8 Readiness Factors for AI Adoption in Agri-food SMEs

This section summarizes the key organizational readiness factors that, according to the literature, influence whether AI applications in SMEs move from pilot testing to stable operation. Organizational readiness can be seen as a shared state where members have a shared commitment to implement change and a shared belief that they can collectively implement it (Weiner, 2009, p. 1). Figure 2.8.1 briefly summarizes the key determinants and outcomes of organizational readiness for change.

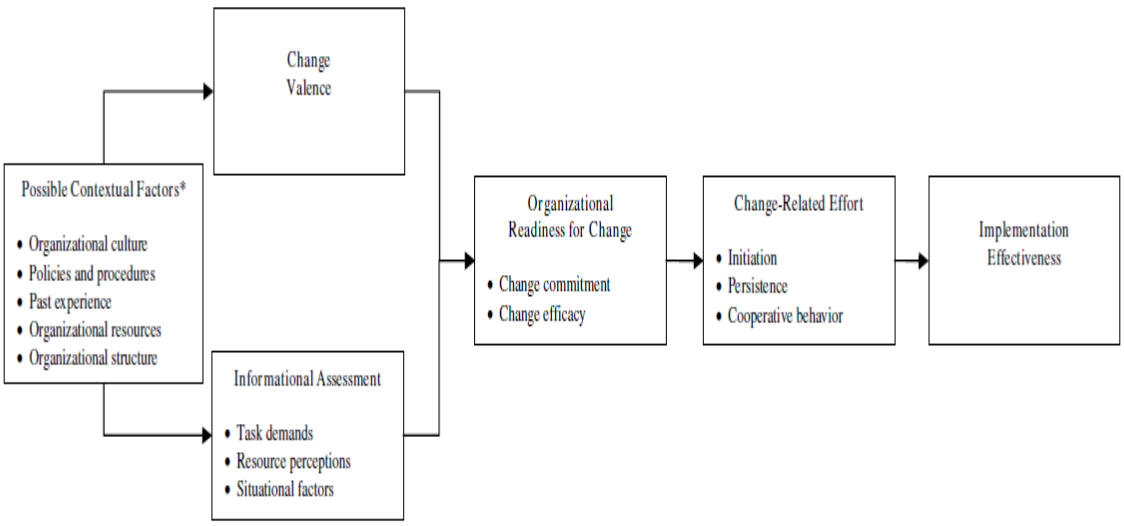

Figure 2.7 Determinants and Outcomes of Organizational Readiness for Change
Note. From Weiner, 2009, Figure 1.

Management commitment/leadership support appears in the literature as critical for successful AI adoption. (Ayinaddis, 2025, p. 10) At the same time, in an empirical study in SMEs the variable "organizational support" —as measured by employee encouragement/motivation/resource practices— was not found to be statistically significant for AI adoption and is attributed to cost and payback barriers. (Badghish & Soomro, 2024, pp. 15, 18) For a grape leaf processing unit, this means that "support" must be reflected in specific implementation decisions (clear pilot scope, roles, resources) that fit the seasonal and pressured production context.

Skills/competences and human capital return as a consistent determinant of adoption: without functional skills, AI is not integrated into routine and remains a tool of the "few". (Ayinaddis, 2025, p. 11) In the same vein, empirical evidence shows a significant impact of "sustainable human capital" on AI adoption. (Badghish & Soomro, 2024, p. 15) In the practice of grape leaf QC, this translates into training and clear roles (e.g., who confirms categories, who checks for deviations, who validates batch acceptance rules when proposed by a model).

Technological fit and perceived benefit influence adoption: relative advantage (relative to other tactics) and compatibility with existing activities are associated with a higher probability of adoption, even when the technology is not perceived as "easy" to learn. (Badghish & Soomro, 2024, p. 15) For the grape leaf company, the benefit must be visible in operational indicators (grading/lot acceptance consistency, reduced rejects/reclassifications, faster documentation at receipt), while compatibility requires the solution to "fit" into the actual batching/acceptance rules and line conditions.

Data readiness and "data pipeline" are a key requirement especially for AgriTech: stable data processing channels are required that are linked to self-learning/improvement of ML algorithms. (Issa et al., 2021, p. 30) Data pipeline here refers to the chain of collection–cleaning/standardization–linking to batches/decisions–storage–disposal for analysis. In grape leaf leaf QC, reliable linking of measurements/images to batches and acceptance decisions is a prerequisite for the system to improve from season to season.

In resource-constrained environments, readiness relies on process standardization, core information systems, and ecosystem support, while AI adoption is proposed as a progressive process with adjustments to structure/culture and not as a one-time project. (Arechavala-Vargas et al., 2025, pp. 45, 51) For the grape leaf case, this supports a realistic scale-up: first stabilize rules/receipt records, then pilot implementation at a controlled point, and then scale up when roles/data/indicators have matured.

Collaborations/partnerships emerge as a practical readiness accelerator, because they give access to technical expertise and resources that are often not available internally in SMEs. (Ayinaddis, 2025, p. 11) In the grape leaf company, this is critical when rapid implementation of data processes and reliable inspection is required within a tight production time window.

2.9 Literature Synthesis: AI Readiness Model for Agri-food SMEs

The synthesis of the literature in sections 2.4–2.8 converges on the fact that “AI readiness” in agri-food SMEs is not a single variable, but a combination of (a) organizational willingness to change and (b) practical implementation capacity. At its core, organizational readiness is understood as a shared psychological state where members are committed to change and confident that they can collectively implement it (Weiner, 2009, p. 1).

At the data level, the readiness model needs a “foundation” of governance and organization, because AI systems require data/metadata that can be located, accessed, linked and reused consistently. The FAIR principles summarize this minimum organizational rule as Findable–Accessible–Interoperable–Reusable, while the emphasis on machine-actionable use means that utilization is not only based on human reading but also on automated consumption by systems (Wilkinson et al., 2016, pp. 3,4).

For agri-food flows, digital readiness is functionally linked to the recording of chain events and data, so that quality control decisions can be documented at batch and movement level. The regulatory logic of Critical Tracking Events and Key Data Elements captures exactly this need: specific chain events and the corresponding data that must be kept as records are defined (U.S. Food and Drug Administration [FDA], 2023, p. 6).

At the level of determinants of adoption, findings in SMEs show that the “whether an AI solution will be implemented” is influenced by (i) the perceived relative benefit and (ii) compatibility with existing workflows/ways of working, while external factors (e.g. government/institutional support) can act as accelerators (Badghish & Soomro, 2024, pp. 14–16). At the same time, the same study shows that a specific indicator of “organizational support" was not statistically associated with AI adoption, so "support" needs careful interpretation in terms of what exactly was measured (Badghish & Soomro, 2024, p. 15).

Therefore, a solid analytical model of AI readiness for agri-food SMEs can be captured as follows:

1. Data readiness (FAIR + event/chain data recording) as a prerequisite for reliable learning/control.

2. Technology–process fit (relative benefit + compatibility) so that the solution is integrated into the flow and does not remain "pilot".

3. Change readiness (commitment + collective effectiveness) as a mechanism that explains whether the organization will persist and stabilize the change implementation over time.

4. Ecosystem readiness through collaborations/partnerships that provide practical support to SMEs, especially when internal resources/know-how are lacking (Ayinaddis, 2025, p. 11).

Connection to the grape-leaf processing unit under study: the model is operationalized into questions/indicators such as: are there stable batch codes and consistent recording of receipt events? Can inspection data (images/measurements/decisions) be tied to batches? Is the operational benefit clear (grading consistency, fewer re-grades, faster decision-making), and is there shared commitment/belief in the ability to support the change during the tight production season?

2.10 Research gap and chapter summary

The review highlighted that AI applications in quality control and especially in incoming receipt/inspection can improve the evaluation and documentation of decisions, but their use requires organizational readiness and "operational" data throughout the chain. In this context, organizational readiness for change is linked to collective commitment and collective belief in implementation capacity (Weiner, 2009, p. 1), while the quality/organization of (meta)data must allow for utilization "by both machines and people" (Wilkinson et al., 2016, p. 4). At the same time, the regulatory logic of traceability (e.g. CTEs/KDEs) shows that, in real food chains, documentation is not a "general principle" but specific facts and data that must be observed (FDA, 2023, p. 6).

Research gaps:

• Gap 1 — Limited understanding of "AI readiness" in SMEs (especially in emerging/resource-constrained environments): While there are studies on digital technologies, it is explicitly documented that there remains a gap in how SMEs specifically approach AI adoption (Arechavala-Vargas et al., 2025, p. 42). Furthermore, AI is not seen as an instant installation but as a progressive process of adaptations to structure and culture (Arechavala-Vargas et al., 2025, p. 51), which is particularly critical in seasonal, high-volume lines such as in the case of the grape-leaf processing unit under study.

• Gap 2 — Inconsistency/Limitations in Empirical Evidence of "Readiness Factors": In an empirical TOE context, factors such as compatibility appear to be statistically significant, while "organizational support" may not show a significant relationship with AI adoption, creating a need to interpret what exactly is measured as "support" and how it translates operationally (Badghish & Soomro, 2024, p. 15). This justifies qualitative investigation at the level of practices (roles, resources, training, data governance), especially for critical batch acceptance decisions at the receiving end.

• Gap 3 — The literature on AI readiness/adoption in the agri-food/AgriTech space remains "immature" and requires synthesis into a workable analytical model: The relevant research is described as "embryonic and underdeveloped" (Issa et al., 2021, p. 13), while broader reviews highlight that "knowledge gaps" remain for "AI integration" strategies and that collaborations/partnerships are a critical form of support especially for SMEs (Ayinaddis, 2025, pp. 3, 12). For a grape leaf company, this translates into a need to connect in a single format: (a) readiness for change/commitment, (b) solution compatibility with real QC flows, (c) data/traceability that "stands" operationally, and (d) access to external expertise when internal resources are limited.

Overall, Chapter 2 shows that the issue for this thesis is not whether AI can be used in quality control. The more important question is what organizational and data conditions would allow AI to be used reliably in incoming inspection. On this basis, Chapter 3 develops the analytical framework of the study. The framework brings together readiness for change, TOE adoption factors such as compatibility and support, and data governance and traceability requirements such as FAIR principles and CTEs/KDEs, so that the empirical analysis of the grape leaf processing unit can be clearly guided.

3 Chapter 3 - Conceptual Framework & Research Hypotheses

The purpose of Chapter 3 is to transform the conclusions of Chapter 2 into a coherent conceptual/analytical framework for the case study (grape leaf processing unit) and to lead to research hypotheses. Such a framework functions as a "map", as it connects the concepts that are considered relevant to the problem and guides the formulation of research questions/hypotheses and the interpretation of the findings. (Imenda, 2014, pp.189–190)

3.1 Linking the LR Findings to the Conceptual Framework

The literature review (Chapter 2) highlighted that the adoption of AI in quality control is the result of a combination of technological, organizational and external conditions, especially when examined at a specific operational point such as incoming inspection in the grape leaf processing unit. Based on this synthesis, the main findings are mapped into three groups of factors that constitute the conceptual framework of Chapter 3:

- Technology (T): adequacy/suitability of QC data, standardization of records, information flows related to batches and inspection results.
- Organization (O): availability of resources and skills, clear roles/responsibilities, QC–production collaboration, possibility of changing processes.
- Environment (E): traceability/compliance requirements, customer/market requirements and external pressures that reinforce the need for more data-driven QC.

Therefore, the Technology–Organization–Environment factors identified in literature review are treated in this framework as determinants of organizational readiness for implementing AI-enabled QC in incoming inspection of the grape leaf processing unit (i.e., shared commitment and shared belief in collective implementation capacity).

This mapping links the main literature review findings to the conceptual framework used in the study. The next sections present the theoretical basis of the framework (3.2), define the key constructs (3.3), introduce the proposed model (3.4), and formulate the research hypotheses (3.5).

3.2 Theoretical Foundation of the Framework

The theoretical foundation of the proposed conceptual framework is based on two complementary lenses: (a) the Technology–Organization–Environment (TOE) model, as a classification scheme of adoption factors at the firm level, and (b) the theory of organizational readiness for change, as a mechanism that explains whether the above factors translate into collective intention and implementation capacity.

The TOE framework documents that the adoption/implementation of innovations is influenced by technological, organizational and environmental factors and that—depending on the technology and implementation context—a specific set of appropriate factors/measures emerges for study (Baker, 2012, p. 6). This scheme is functional for the specific case study, where the introduction of AI-enabled quality control in a grape leaf processing unit simultaneously requires (i) technical feasibility and infrastructure, (ii) organizational adaptation of processes/skills and (iii) responsiveness to external requirements (e.g. customers/markets/standards). In the specific grape leaf processing unit, the TOE is "translated" into: Technology (availability/quality of data and technical infrastructure for AI-QC), Organization (standardization of the receiving flow–QC, skills and management support) and Environment (customer/market requirements, compliance and technology supplier ecosystem).

In this thesis, TOE is used to organize the factors that may influence AI readiness: technology, organization and environment. Organizational readiness is treated as the outcome to be examined. Following Weiner (2009, p. 1), readiness includes two dimensions: change commitment and change efficacy. In practical terms, the study examines whether staff and management see AI-supported QC as worth pursuing, and whether they believe the company has the capacity to implement it under real production conditions. Following Weiner (2009, p. 4), the assessment of task demands, resource availability and situational factors is used to interpret change efficacy, not as a separate group of variables outside the TOE framework.

Finally, the theoretical choice is also supported at the operational level: the study by Shea et al. offers psychometric documentation for a short, theory-based measure of organizational readiness (ORIC) and empirically confirms the distinction of the two aspects (commitment/efficacy) as two correlated factors with a good fit of the measurement model (Shea et al., 2014, p. 12). This is crucial so that "readiness" does not remain an abstract concept, but is linked to a specific way of discussion/evaluation in the empirical part of the work.

3.3 Key Constructs and Definitions

This section defines with operational clarity the key constructs used in Figure 3.1, in order to (i) distinguish what constitutes an independent framework of determinants (TOE context factors) and what constitutes the dependent outcome of the study (Organizational readiness), and (ii) avoid conceptual overlap between "factors" and "readiness dimensions".

TOE context factors (independent framework). The TOE framework organizes the determinants of the business environment into three distinct domains—technology, organization, environment—that are linked to technology adoption/integration decisions (Justino et al., 2022, p. 2). In this study, the TOE context factors function as the independent framework within which to examine how Organizational readiness for AI-supported quality control is shaped in the case under consideration.

Organizational readiness (outcome). Organizational readiness is defined as a collective state of readiness for organizational change and is composed of two dimensions: change commitment and change efficacy (Weiner, 2009, p. 2). Its capture in the case is done with group-referenced formulations (e.g., "we as a unit…") in order to capture collective readiness and not individual attitude (Shea et al., 2014, p. 2).

Change commitment. Change commitment concerns the extent to which members share a common resolve to proceed with change (shared resolve) (Weiner, 2009, p. 2). In practice, in this context, it captures the shared intention to organizationally support the transition to AI-supported QC (e.g. acceptance of new QC recording/decision disciplines). The intensity of change commitment is related to the extent to which members collectively value the change as sufficiently "worthy" to commit to its implementation (change valence) (Weiner, 2009, p. 4).

Change efficacy. Change efficacy refers to the collective belief that the organization can organize and execute the actions required to successfully implement the change (shared beliefs in collective capabilities) (Weiner, 2009, p. 2).

Determinants of implementation capability (under change efficacy). According to Weiner, judgments of change efficacy are shaped by three determinants of implementation capability: task demands, resource availability, and situational factors (Weiner, 2009, p. 4). These determinants do not constitute an additional independent "block" beyond the TOE; they are used analytically to explain how TOE context factors translate (or do not translate) into higher/lower change efficacy in the specific case.

Organizational AI readiness factors. The relevant literature organizes organizational readiness for AI into categories of factors such as strategic alignment, resources, knowledge, culture, data (Jöhnk et al., 2021, p. 6). In this study, these categories are used as a short terminology "bridge" to the TOE: conceptually they correspond mainly to Technology (especially data) and Organization (especially resources/knowledge/culture/strategic alignment), while aspects of them may also be linked to Environment when they express external requirements/expectations that frame the adoption.

Data quality (fit-for-use). Data quality is defined as the extent to which the inherent characteristics/values of data follow rules/constraints that make them fit-for-use (Miller et al., 2024, p. 9). It is included in the Technology context factors, as it directly affects the ability of AI to reliably support QC decisions.

Traceability. Traceability is defined as the ability to distinguish, identify and track the movement of a food/substance through all stages of production, processing and distribution (FAO, 2017, p. 4). It is primarily treated as an Environment context factor (external demand/market expectation/compliance), which however requires technological implementation (information/data flows) and organizational discipline in data collection.

3.4 Proposed Conceptual Model

Based on the definitions in section 3.3 and the findings of the literature review, the proposed conceptual model is depicted in Figure 3.4.1. The model places organizational readiness for implementing AI in quality control at the receiving stage of the grape leaf processing unit as a dependent outcome and examines how the three categories Technology–Organization–Environment (TOE) function as determinants that influence this readiness. Accordingly, the empirical part of the study examines how unit stakeholders describe these factors and their connection with readiness for implementation. The corresponding research hypotheses/analytical propositions are formulated in section 3.5.

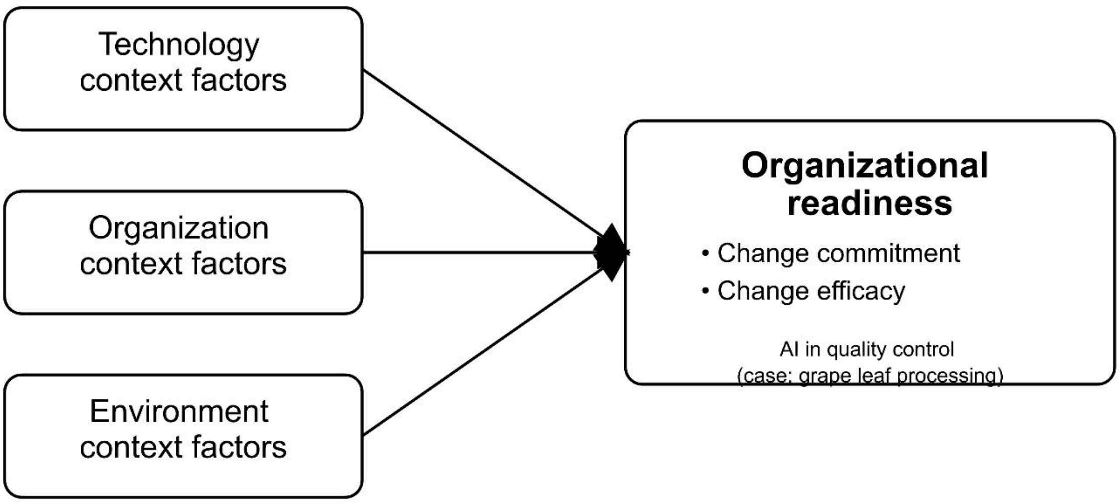

Figure 3.1 Proposed Conceptual Model

- Technology (T): Quality/standardization of QC data and technical capability to collect–organize data that AI requires to support the receiving flow.
- Organization (O): Internal standardization of processes, allocation of roles/responsibilities and organizational capabilities that allow for consistent QC execution and recording.
- Environment (E): External requirements (market, customers, compliance) that push for documentation/traceability and shape the QC specifications that AI is called upon to support

3.5 Research Hypotheses

In this qualitative case study (grape leaf processing unit), the Research Hypotheses serve as focal guides for data collection and interpretation, focusing the investigation and setting clear boundaries in the field of empirical analysis (Baxter & Jack, 2008, p. 552). A central dependent concept is organizational readiness for change, which is defined as the shared commitment of members to implement change (change commitment) and their shared belief that they have the collective ability to implement it (change efficacy) (Weiner, 2009, p. 1).

3.5.1 Technology-Related Hypothesis (H1)

For AI-enabled QC, technological readiness is not limited to the existence of digital tools, but concerns whether the inspection process produces data that are structured, reliable and usable for decision-making. Jöhnk et al. (2021, p. 11) link AI readiness with process fit, noting that AI-based systems work better when processes are standardized and provide structured data input. This is also consistent with the data-readiness perspective: FAIR data principles emphasize machine usability and reuse of data (Wilkinson et al., 2016, pp. 1, 3), while data quality depends on dimensions such as accuracy, timeliness, completeness and reliability (Mansouri et al., 2021, p. 2). In AgriTech, Issa et al. (2022, p. 36) further stress that AI adoption requires raw data to be extracted, filtered, organized and translated into workable formats. Therefore, in the present case, the technological basis of readiness depends on whether incoming inspection can produce standardized, consistent and batch-linked QC data that can support reliable AI-assisted acceptance, rejection or classification decisions.

H1 (Technology): The degree of structured/standardized processes and data in incoming inspection is related to the organizational readiness for implementing AI-enabled QC in the grape leaf processing unit.

3.5.2 Organization-Related Hypothesis (H2)

Organizational readiness also depends on implementation capacity. For AI-enabled QC, management support is not enough if it is not translated into time, people, skills and clear responsibility. Weiner (2009, p. 4) links change efficacy to the organization's assessment of task demands, resources and implementation conditions. In AI readiness studies, similar issues appear as top management support, training, upskilling and interdisciplinary capabilities (Jöhnk et al., 2021, pp. 11, 13). Evidence from SMEs also shows that human capital is important for AI adoption, while general organizational support matters only when it becomes practical resources, skills and implementation capacity (Badghish & Soomro, 2024, pp. 5–6, 14–15). In the present case, this leads to the following organization-related hypothesis.

H2 (Organization): The strength of management support and the adequacy of resources/capabilities for change (e.g. time, human resources, QC–IT–production skills) are related to organizational readiness for implementing AI-enabled QC in incoming inspection.

3.5.3 Environment-Related Hypothesis (H3)

For the environmental dimension, the issue is not simply whether external pressure exists, but whether such pressure makes better-documented QC decisions more necessary. In the TOE framework, the environmental context includes industry conditions, technology service providers and the regulatory environment (Baker, 2012, p. 5). In food supply chains, this is closely linked to traceability. GS1 (2017, p. 9) identifies market pressures and emerging regulations as key drivers of traceability, while FAO (2017, p. 7) stresses the need to link the physical flow of products with the flow of information about them. The FDA traceability rule follows a similar logic through Critical Tracking Events and Key Data Elements, where supply-chain events are connected with specific data records (FDA, 2023, p. 6). In the present case, customer expectations, market pressure and compliance-oriented documentation may therefore strengthen the perceived need for more objective, traceable and data-supported QC decisions at incoming inspection.

H3 (Environment): The intensity of external requirements for traceability/compliance and quality documentation is related to organizational readiness to implement AI-enabled QC in incoming inspection in the grape leaf processing unit.

3.6 Chapter Summary and Transition to Methodology

Chapter 3 transformed the synthesis of the literature review into a coherent conceptual framework that specifies the adoption of AI in quality control, with an emphasis on the raw material receipt/initial inspection stage in the case study of a grape leaf processing unit. The choice of TOE allowed the critical adoption factors to be organized at the technological, organizational and environmental levels, while the focus "locked" on the core of organizational readiness as a prerequisite for reliable implementation.

Centrally, organizational readiness is understood as a shared psychological state of members, where commitment to implement the change and confidence in the collective ability to implement it coexist (Weiner, 2009, p. 1). On this theoretical foundation, the Research

Hypotheses of 3.5 act as focal analytical propositions that guide data collection and discussion/interpretation, determining the direction and scope of the empirical investigation (Baxter & Jack, 2008, p. 552).

Based on the above, Chapter 4 presents the methodology of the study. A qualitative case study design was adopted, as this approach is suitable for the in-depth exploration of complex issues in a real organizational setting (Crowe et al., 2011, p. 1). The study was based mainly on semi-structured interviews, supported where relevant by internal QC material, while the interview protocol was refined through alignment with the research objectives, feedback and field testing (Castillo-Montoya, 2016, p. 827).

4 Chapter 4 - Research Methodology

4.1 Methodology Overview and Research Design Rationale

This section summarizes the methodological approach and justifies the research design in relation to the research questions. The following sections of Chapter 4 present the research design, data collection method and analysis process in detail.

Qualitative research is exploratory in nature and is particularly suitable when the researcher does not know in advance all the critical variables and seeks to understand phenomena “as they are experienced” within their natural context. Furthermore, it is based on a rich, detailed description and in-depth recording of the experiences of the participants, utilizing their own narratives as a key source of data (Chowdhury, 2021, p. 192-193).

In this context, the case study is an appropriate research strategy. At a practical level, the research was implemented as a qualitative single-case study based mainly on semi-structured interviews with key informants from functions related to quality control. Where relevant, internal sources such as procedures, forms and QC logs/master files were used to support the interview evidence. Qualitative data were analyzed through thematic analysis, while trustworthiness measures are summarized in the following sections.

4.2 Research Design: Qualitative Single-Case Study

This study adopts a qualitative research design in the form of a single-case study, as the research object—organizational readiness for adopting AI in quality control—constitutes a complex and contemporary organizational phenomenon that must be understood within its real context. The qualitative case study supports the in-depth investigation of such phenomena, utilizing more than one perspective/source so that the issue is not examined in a one-dimensional manner but that different aspects of it are revealed. (Baxter & Jack, 2008, p. 544).

Furthermore, according to Yin – as summarized by Baxter and Jack (2008) – a case study design is particularly appropriate when the research interest focuses on “how” and “why” questions, when the researcher cannot control the behavior of those involved, and when the boundaries between phenomenon and context are not clear (Baxter & Jack, 2008, p. 545).

Based on the above, the design is chosen as a single-case because the aim is to gain an in-depth understanding of readiness at the organizational level (unit of analysis: organizational readiness) and not to compare multiple organizations. Although the single-case approach can be implemented either as holistic or as embedded, in this study the holistic single-case design is preferred, so that the different voices (e.g. Administration, Production, QC) can function as complementary perspectives on the same organizational phenomenon, without the analysis being "broken" into sub-units and moving away from the central research question. (Baxter & Jack, 2008, p. 549).

Finally, the case study design requires a clear "binding" of the case in order to maintain focus and a manageable scope (Kodithuwakku, 2021, p. 182); the analytical delimitation of the case (case context and case boundaries) is presented in the following section 4.3.

4.3 Case Context, Case Boundaries, and Scope & Delimitations

4.3.1 Case Context and Case Boundaries

This study is conducted in the context of a grape leaf processing company and focuses on organizational readiness for potential adoption of AI applications in quality control (QC). In the case study methodology, a "case" is defined as a phenomenon examined within a bounded context and corresponds to the basic unit of analysis (Baxter & Jack, 2008, p. 545).

To prevent an overly broad and unmanageable scope, the literature suggests setting clear boundaries that define what is and is not studied, as well as the breadth and depth of the investigation (Baxter & Jack, 2008, p. 547). The case study approach also helps delimit the relevant data/information, not only the participants, through physical/geographical, social and time boundaries (Kodithuwakku, 2021, p. 182).

Based on the above, the boundaries of the study are defined as follows:

- Organisational / Social boundary: The unit of analysis is the specific organisation (bounded context), while the "social boundary" is defined as the key roles/functions directly linked to QC and the relevant decisions (Administration, Production, QC), in order to capture complementary perspectives within the same organisational framework

- Time boundary: The time frame is delimited to the last completed production period May–early August 2025, while the interviews were conducted in March 2026 to support a reflective recording of practices and experiences in relation to a specific season.
- Data / information-gathering boundary: The main source was semi-structured interviews. Where relevant, selected internal QC documents, such as internal procedures, forms and QC master reports/files, were used only to support documentation and comparison across interviews. The use of multiple data sources is a characteristic of the case study and can enhance the reliability of the findings (Baxter & Jack, 2008, p. 554), provided that the scope remains limited to avoid data overload.
- Analytical boundary: The analysis focuses on organizational readiness for AI in QC, in line with the research questions and conceptual framework of Chapter 3, without technical evaluation of AI models.

4.3.2 Scope, Delimitations and Limitations

Scope. The scope of the study concerns the organizational readiness for adopting AI in quality control within the context of the specific company/case.

Delimitations. The study does not include: (i) technical evaluation/benchmarking of AI algorithms, (ii) full economic and technical valuation (e.g. ROI), (iii) systematic comparison between individual factories/units (multi-site comparison), and (iv) participation of line workers, suppliers or customers as key informants.

Limitations. Possible limitations relate to the availability of executives (workload/time planning) and to the fact that part of the interviews is based on a retrospective description of practices from the 2025 season.

4.4 Data Collection: Semi-Structured Interviews

4.4.1 Purpose of the Interviews and Link to Research Questions

The primary data collection was based on individual semi-structured interviews, as the research sought depth and understanding in areas that are not easily “measurable” with quantitative approaches, such as perceptions, practices and experiences around organizational readiness for AI in quality control (Gill et al., 2008, p. 295). The interviews provided in-depth information on existing QC routines and the conditions for change/adoption of new solutions (DiCicco-Bloom & Crabtree, 2006, p. 319).

4.4.2 Interview Type Selection: Semi-Structured

The semi-structured format was chosen to ensure a common core of topics (comparability between roles) and at the same time flexibility for in-depth exploration when critical details or examples from practice emerge. The quality of data collection is enhanced when the interview guide is developed in a systematic manner and the logic of the choices made is documented (Kallio et al., 2016, pp. 2961- 2963).

4.4.3 Interview Mode, Setting, and Practical Arrangements

Interviews were conducted primarily in person, or by telephone/remotely where required, with the aim of understanding the responses and maintaining the flow. The choice of method took into account that, when "social cues" are important for the type of information sought, in-person or telephone interviews are preferable (Opdenakker, 2006, para. 44). In practice, interviews targeted key informants from Management, Production and QC, in order to capture complementary perspectives on the processes, decisions and constraints that affect AI readiness in QC.

4.4.4 Development of the Interview Guide

The interview guide was developed based on the research questions and the dimensions/constructs of Chapter 3. The process followed the literature's recommendation for structured development and justification of the researcher's decisions when preparing a semi-structured guide (Kallio et al., 2016, p. 2963). Before the main data collection, the guide was tested and optimized through internal review, peer review and field testing (Kallio et al., 2016, p. 2960).

4.4.5 Conduct of the Interview

The interviews followed a consistent flow (opening–main topics–probing questions–closing), with emphasis on practices and specific examples from the QC/production function. The process relied on active listening and clarifying questions to clarify terms, roles and critical processes without leading.

4.4.6 Recording, Note-Taking, Transcription, and Data Management

Audio recording was included in the interview protocol only where explicit consent was provided. The literature points out that maintaining high-quality audio recordings and practicing with the recorder before using it in the field are critical, while specific consent for recording is often required (DiCicco-Bloom & Crabtree, 2006, p. 318). In practice, no participant consented to audio recording. Therefore, the interviews were documented through detailed notes taken during and immediately after each interview. These notes were then anonymized and used as the empirical material for thematic analysis. The interview notes and related analysis files were stored in a way that supported anonymization and controlled access.

4.5 Sampling Strategy and Participants

4.5.1 Purposeful sampling and selection criteria (Key informants)

The present study adopted purposeful sampling in order to select participants who are “information-rich” with respect to the phenomenon under study, namely organizational readiness for the adoption of artificial intelligence in quality assurance/quality control in a grape leaf processing unit. “Purposeful sampling is a technique widely used in qualitative research for the identification and selection of information-rich cases for the most effective use of limited resources” (Patton, 2002, as cited in Palinkas et al., 2015, p. 2). The sampling logic is explicitly linked to the conceptual framework and research questions, while it is clearly documented and described in terms of “why” and “who” participate. (Palinkas et al., 2015, pp. 6-7, 10).

The selection of participants followed the logic of "key informants". As Laforest (2009, p. 2) explains, key informants are "privileged witnesses" who, due to their position, activities or responsibilities, have special knowledge about the problem under study and can offer access to perceptions and concerns that are not immediately visible. In the context of this research, organizational stakeholders are considered executives and employees who are directly linked to quality control, production, information systems and strategic development of the company. Semi-structured interviews with these "key actors" therefore function as a basic tool for understanding organizational readiness for the adoption of AI in quality control.

4.5.2 Sample size rationale (Information power)

The sample size was not defined as a "fixed number in advance", but was justified based on the principle of information power, according to which the more relevant information the sample "holds" in relation to the study objective, the smaller the required N can be (Malterud et al., 2016, p. 1753).

Therefore, the study included six semi-structured interviews, with attention to the contribution of the data per thematic category and functional role, in order to ensure adequate coverage of critical dimensions of organizational readiness (administration/governance, production, quality and related support functions where required).

4.5.3 Participant groups, recruitment and access

Participants came from roles that reflect the main organizational "actors" of the phenomenon: (a) Administration/Management, (b) Production, and (c) Quality Control. This allowed the study to capture both strategic/administrative and operational/technical perspectives on AI readiness in quality control. Access was achieved through targeted invitation to appropriate key informants, with inclusion criteria being relevant involvement in quality/production/decision-making processes and direct knowledge of existing practices and limitations.

4.6 Data Analysis and Research Quality (Trustworthiness)

The interview data were analyzed using thematic analysis, a method that aims to identify, analyse, organise, describe and report themes within a data set (Nowell et al., 2017, p. 2). In this study, a theme is understood as a pattern of meaning that "captures something important" in relation to the research question and represents a level of patterned response/meaning in the data set (Braun & Clarke, 2006, p. 10).

The analysis was organized in distinct phases: familiarisation, initial coding, theme development, review/refinement, naming/defining and write-up. Familiarisation involved repeated reading to gain an overall picture of the corpus and identify initial indications of meanings/patterns before coding began (Braun & Clarke, 2006, p. 16). Initial coding then assigned short labels to text fragments, in order to group units of meaning and support the development of themes. The process was recursive rather than linear, as the researcher moved between the overall data, coded fragments and the emerging interpretation (Braun & Clarke, 2006, p. 16).

Regarding the coding logic, a hybrid approach was followed: deductive codes aligned with the dimensions of the conceptual framework (Chapter 3), while inductive codes captured issues that emerged from the field. This choice is functional, as engagement with the literature in the early stages varies depending on whether the analysis is more inductive or more theoretical (Braun & Clarke, 2006, p. 16). On a practical level, the interview notes were anonymized and organized into a single corpus, while Microsoft Word and Microsoft Excel supported the codebook and "quote–code–theme" tables.

The analysis was supported by systematic documentation and trustworthiness measures. An audit trail was maintained for the main analytical decisions, such as code definitions, merging/separation of codes and reformulation of themes, as it provides evidence of the researcher's decisions during the study (Nowell et al., 2017, p. 3). Reliability was considered through the criteria of credibility, transferability, dependability and confirmability (Shenton, 2004, p. 73). Credibility was supported by comparing views from different functional roles (Administration/Management–Production–QC), while transferability was supported through description of the organizational context, including production flows, QC practices and data/system constraints (Shenton, 2004, pp. 66, 73). Dependability and confirmability were supported through the codebook, audit trail and short reflexive notes. Finally, the SRQR checklist was used as a supplementary reporting tool and the completed checklist is listed in Appendix E (O'Brien et al., 2014, p. 1248; Tong et al., 2007, p. 356). The interview guide is presented in Appendix A, the illustrative codebook extract and coding trail in Appendix D, and the completed SRQR checklist in Appendix E.

4.7 Ethical considerations and data protection

The research was conducted with emphasis on voluntary participation and avoidance of pressure or undue influence, particularly due to the work context (Economic and Social Research Council, 2015, p. 4). Before each interview, participants received clear information on the purpose, procedures and intended use of the data, so that consent was informed (Economic and Social Research Council, 2015, p. 4). Interviews could be recorded only after explicit consent, as participants have the right to refuse recording devices (British Sociological Association, 2017, p. 6). Since no participant consented to recording, detailed notes were kept.

To protect confidentiality and anonymity, interview notes and analysis files were stored in a personal, secure environment of the researcher with exclusive access, while direct identifiers were removed and pseudonyms/codes were used (British Sociological Association, 2017, p. 7). Consent forms were kept separate from the research corpus, so that they were not linked to interview notes or excerpts (British Sociological Association, 2017, p. 7). When citing excerpts, care was taken to avoid direct or indirect identification of participants, especially in roles with a limited number of people. Regarding the GDPR, processing was carried out with appropriate security/confidentiality and data retention was limited to the period necessary for the purposes of the research (European Parliament and Council of the European Union, 2016, Article 5(1)(e)–(f), L 119/36).

The participant information sheet and consent form are presented in Appendix B, while the concise data management plan is presented in Appendix C.

5 Chapter 5 - Data Analysis

5.1 Introduction to the empirical analysis

This chapter presents the empirical findings of the research, which emerged from six semi-structured interviews with participants from three key functional areas of the company under consideration: Management, Production and Quality Control. In line with the qualitative design of the case study, the analysis focuses on participants directly involved in processes related to quality, production and decision-making, in order to capture complementary strategic and operational perspectives regarding organizational readiness for AI adoption in quality control.

Consistent with the analytical approach presented in Chapter 4, the interview material was analyzed through thematic analysis, following an iterative process of familiarization with the data, initial coding, theme development, revision and clarification of the themes, as well as a final synthesis of the findings. A hybrid coding logic was followed, combining deductive codes linked to the conceptual framework of the study and inductive codes derived from the field data itself. At the same time, the interviews were anonymized and organized into a single corpus, in order to support a transparent and traceable analytical process.

The findings are presented around the main themes and sub-themes that emerged from the interviews. Section 5.2 addresses Obj1/RQ1, Section 5.3 addresses Obj2/RQ2, and Sections 5.4 and 5.6 relate mainly to Obj3/RQ3. Section 5.5 compares the views of Management, Production and Quality Control, in order to identify both recurring patterns across the data set and differences between functional roles. This comparison also supports the trustworthiness of the analysis. The focus remains on organizational readiness for adopting AI in quality control, not on the technical evaluation of specific AI systems or on quantitative assessment of economic outcomes.

For anonymity purposes, participants were coded according to their functional group as follows: MG1–MG2 for Management, PR1–PR2 for Production, and QC1–QC2 for Quality Control. Participants were selected so as to reflect some variation in organizational position, including different company units and, in the case of Quality Control, different shifts.

5.2 Current QC system and digital practices

This section addresses Obj1/RQ1 by examining how QC is currently organized in the case company and how data and digital tools are used in practice. The QC system focuses mainly on the inspection and classification of incoming grape leaves, but it also includes checks of raw, auxiliary and packaging materials, monitoring of key production parameters, and evaluation of the final product before shipment. Across the interviews, the receiving stage emerged as the most critical point of control. This is where the first decisions are made on whether a load will be accepted, rejected, or directed to a different recipe or handling route. These decisions are often made under time pressure and in direct interaction with suppliers.

In daily operation, the current QC system is still strongly dependent on people. Incoming inspection follows predefined specifications, but the actual assessment often relies on experience and visual judgement, especially for characteristics such as colour, size, shape, tenderness, damage and general leaf conformity. This dependence becomes more important during receiving, where baskets need to be checked quickly so that trucks are not delayed and suppliers do not feel that the process is unfair or inconsistent.

Participants also made clear that not all QC decisions depend on the same type of judgement. The first receiving check is faster and more visual, while later sample examination and sensory assessment allow more detailed comparison with specifications. Laboratory control adds another layer, since it includes basic analytical tests and equipment-based measurements. For this reason, the current system should not be described as purely informal or experience-based. It combines formal specifications, practical judgement and some measurement-based controls, but the first receiving decision remains the point where human experience has the strongest influence.

This dependence on people is also reflected in the way QC and production data are recorded. The company already captures useful information, including weighing data, traceability details, production forms, supplier scoring and selected laboratory results. However, these records are not handled in the same way across all functions. Several participants described a mixed paper-and-digital practice, where information is first written by hand and only later transferred to digital form when it is needed for reporting, analysis or traceability. This applies especially to

QC and laboratory records, but also to parts of production documentation. As a result, the company does not lack operational or quality-related data; the main issue is that much of this data remains fragmented, partly handwritten and not always ready for systematic use.

A further issue concerns the practical limits of current data capture. Several interviewees pointed out that important aspects of quality are not easily observable or measurable at the reception stage. Because the leaves are tightly packed vertically in the baskets, only the upper visible part can be inspected quickly, while problems concerning the rest of the leaf body or foreign matter in the lower part of the basket may not be immediately detected. At the same time, some useful parameters are not yet measured precisely in-house. One example is leaf moisture, which is difficult to assess accurately through experience alone and would require additional equipment. More broadly, some measurements are either not currently available in-house or are limited to simple and fast analyses, while in more complex cases external laboratory support is required. This means that, despite the existence of a structured QC routine, the current system operates within clear informational and technological constraints, which further reinforce the dependence on human experience and rapid judgment under pressure.

Overall, the current QC system and the associated digital practices can be characterized as operationally established but only partly digitalised. They combine formal specifications, practical know-how, mixed recording practices and limited real-time visibility into certain quality parameters. This creates a working environment in which QC and production decisions are functional and routinised, but are still strongly influenced by subjectivity, time pressure, partly manual recording practices, and limited digital integration. These characteristics are an essential part of the company's current baseline and constitute the immediate organizational context within which the potential role of AI is then examined.

5.3 Perceived opportunities and challenges of AI in QC

To address Obj2/RQ2, this section focuses on how participants understood the possible use of AI in QC. In the interviews, AI was discussed mainly in relation to incoming inspection. This is the point where quality decisions have to be made quickly, while the company is also dealing directly with suppliers and incoming loads. For this reason, participants did not describe AI in broad or abstract terms. They mainly linked it with faster checking, more reliable classification, and more objective decisions on whether leaves should be accepted, rejected, or directed to another handling route.

Across the interviews, participants often returned to the same point: AI could reduce part of the variation that comes from human judgement. Participants connected its possible value with more stable application of specifications and with decisions that would be easier to explain and document. This was especially important for receiving, because decisions at this stage can affect supplier payments and the perceived fairness of the process. In this sense, AI was not seen only as a tool for automation. It was also seen as a possible way to make quality decisions more consistent and less dependent on the judgement of one person at one moment.

Participants also linked AI with better use of information beyond the first inspection. Existing data on traceability, supplier performance, production follow-up and laboratory results could become more useful if they were connected and analysed more systematically. Seen in this way, AI would not only support acceptance or rejection at receiving, but could also help with broader monitoring and decision-making. Some participants saw value in understanding how leaf quality, recipes, production conditions and final product outcomes are connected. This shows that the expected role of AI was not limited to replacing a manual check, but also included better use of QC and production knowledge.

The reservations were also clear. The main concern was whether an AI-supported system could work under the actual receiving conditions of the company. The process has to be fast, the leaves are packed tightly in baskets, and only part of the material can be seen during the first check. Participants therefore questioned whether the technology could inspect the material reliably without slowing down the flow or creating new practical problems. The concern was not a general rejection of AI. It was mainly a question of practical fit.

Another concern was the human and organizational side of adoption. AI is still unfamiliar in this working environment, and participants did not always have a clear picture of how such a system would operate in daily work. Training would therefore be necessary, but training alone would not solve the issue. The company also works with seasonal pressures and, in some roles, seasonal staff. This creates a risk that knowledge and familiarity with a new system may not be maintained from one production period to the next.

The same caution appeared in business terms. AI would have to improve quality control, support the production flow, and create useful information with measurable benefit, without adding excessive cost, complexity or implementation burden. For this reason, AI appears as a promising but conditional option. Participants recognized its possible value for speed, objectivity, consistency, monitoring and decision support, but its acceptance depends on whether it can prove useful in the company's real operating conditions and be introduced gradually.

5.4 Organizational readiness factors

The previous section showed that AI was viewed as useful only under certain conditions. This section moves from perceived value to organizational readiness. In relation to Obj3/RQ3, the interviews suggest that readiness in the company is not a simple yes-or-no condition. It is shaped by the way technological, organizational and environmental factors come together in daily QC work. The analysis therefore follows the study's TOE framing: technological factors (H1), organizational factors (H2), and environmental factors (H3). This structure helps show which parts of readiness are already present and which parts still need development.

The technological side gives a mixed picture. The company already keeps several types of operational and quality-related records, including basic traceability information and data from receiving, production and QC activities. This provides an initial basis for future digital use. However, the interviews also showed clear limits. Many records are still handwritten or only later transferred into digital form, and the information is not always organized in a way that would support AI-assisted incoming inspection. There are also practical limits at receiving: visibility inside baskets is partial, some useful parameters cannot yet be measured accurately in-house, and more complex checks may require external laboratory support.

The technological evidence points in two directions. Existing records and traceability practices create a starting point for AI-related development. At the same time, the data are not yet structured, consistent or integrated enough to make AI adoption straightforward. A future AI initiative would therefore begin from a working but uneven data base, not from a fully digital QC environment.

The organizational side is mainly about people, routines and the company's ability to absorb change during daily work. QC and Production rely strongly on experience, practical knowledge and quick adjustment, especially during the receiving period. This is useful, because experienced staff can respond quickly when problems appear. It is also a limitation, because decisions may differ depending on who is available, how much pressure exists at that moment, and how familiar each person is with the quality criteria. Seasonality makes this issue more important, since staff continuity, skill retention and familiarity with any new system cannot be taken for granted.

For this reason, organizational readiness is not only a matter of willingness to use AI. It also depends on whether people have enough time, training, routines and internal support to use it in practice. Limited familiarity with AI means that staff would need to understand not only how to operate a system, but also how its outputs should be used in QC decisions. This is especially important in incoming inspection, where decisions have to be fast, practical and accepted by the people involved in the process.

Management support is part of the same organizational picture. Management participants connected AI with better quality performance, stronger control, improved traceability and better use of information. Still, support at strategic level does not by itself create readiness. A future AI initiative would require clear decisions, a realistic feasibility assessment, responsible people, training and follow-up. The company's direction is therefore compatible with an AI-supported QC initiative, but the implementation path is not yet fully defined. The missing element is not only a suitable technical solution. It is also the internal structure that would turn general interest into a manageable project.

The environmental side adds a different type of pressure. Participants mainly linked this pressure with customer expectations for stable quality, fewer defects, stronger traceability and reliable documentation. Competitive pressure also matters, because the company needs to maintain quality without adding unnecessary cost or complexity. Supplier relations make the receiving stage even more sensitive. Decisions at this point affect acceptance, rejection and payment, so any new system would need to support not only internal control but also the perceived fairness and credibility of the inspection process.

Some participants also connected the broader environment with regulatory and market-related pressures, especially around recipe composition, food safety requirements and the need to adapt to changing external expectations. These pressures strengthen the case for better QC documentation, consistency and traceability. However, they do not make AI adoption easier by themselves. Environmental factors therefore appear mainly as a pressure to improve rather than as an immediate support mechanism: they reinforce the need for change, but they do not remove the internal work needed before AI can be adopted.

The picture that emerges is one of conditional readiness. The company has useful operational experience, basic data and a clear practical reason to improve QC, but these strengths are balanced by gaps in data structure, staff continuity, AI familiarity and implementation planning. AI adoption in QC would therefore need to begin as a controlled and well-supported change, rather than as a direct move to full automation.

5.5 Cross-role convergence and divergence

After the analysis of readiness factors, it is useful to look at whether the same picture appears across the three interview groups. This section compares the views of Management, Production and Quality Control, focusing on where their views converge and where each role gives different emphasis.

The strongest point of convergence concerns the receiving stage. All three groups treated incoming inspection as the most critical point in the current QC process. They also recognized that the system still depends heavily on human judgement and that AI could have value if it improved the objectivity, consistency and speed of decisions. There was also a shared sense that the company is not yet fully ready for such a change. Training, gradual adaptation and careful implementation were seen as necessary before any serious adoption effort.

The differences appear more clearly in the way each group understood the main value and risk of AI. For Quality Control, the key issue was practical reliability at receiving. AI would be useful only if it could support faster and more consistent inspection and sorting without slowing down the reception process or weakening the reliability of quality decisions. For Production, the issue was broader. Participants linked AI not only with inspection, but also with incoming leaf quality, production adjustments, recipe handling and use of resources. From this view, the main concern was how the technology would fit into the actual production flow without losing the value of practical experience.

Management viewed AI from a more strategic and implementation-focused position. The main questions were feasibility, value for money, pilot use, internal coordination and long-term business value. From this perspective, acceptance by people is important, but it is not the only issue. Management also needs confidence that the technology is mature enough, that it can be introduced through a credible implementation path, and that it can produce a real business return.

Taken together, the comparison shows that the three groups share the same basic diagnosis: the current system is human-dependent, incoming inspection is the key pressure point, and AI could support improvement. The differences are not contradictions. They reflect the priorities of each role. QC focuses on inspection reliability, Production on process fit, and Management on feasibility and return. This means that readiness is partly shared across the company, but it is not experienced in exactly the same way by all functions.

5.6 Integrated readiness profile of the case company: change commitment and change efficacy

This section brings together the findings of the previous sections into an overall readiness profile of the company, with emphasis on the two main dimensions of organizational readiness: change commitment and change efficacy. It further addresses Obj3/RQ3 by showing how the influence of H1–H3 is reflected through these two readiness dimensions. The empirical material does not point to a company that is either clearly ready or clearly unready for AI adoption in QC. Instead, it shows a partial and uneven readiness profile, where recognition of the possible value of AI coexists with doubts about its practical applicability.

The first part of this profile concerns change commitment. The company shows interest in AI, but this interest is conditional. All three functional groups recognized that the current QC system has limits in objectivity, consistency, speed and systematic use of data. They also saw possible value in AI for incoming inspection, monitoring, traceability and broader decision support. From the Management side, AI was also connected with strategic priorities, such as quality leadership, stronger process control and improved efficiency. Even so, AI was not treated as an automatically desirable change. Participants expected it first to prove that it can work reliably, fit the real receiving process and offer clear business value.

The second part concerns change efficacy, where the picture is weaker. The company has practical know-how, a quality-oriented culture and some basic data infrastructure, but these conditions are not yet enough to support direct implementation. Data practices are still partly manual, some records remain handwritten, in-house measurement is limited, and seasonal staffing makes knowledge continuity difficult. Familiarity with AI is also limited, while training, gradual adaptation and clear internal responsibility would be needed. Participants also raised doubts about whether the technology could fit the receiving environment in practice. For this reason, even when AI is seen as potentially useful, the belief that the company can already implement it effectively remains limited.

The resulting readiness profile is therefore one of conditional commitment but weaker efficacy. In other words, the company seems to recognise that an AI-supported improvement in QC could have value, but it does not yet show a strong enough belief that the necessary conditions for immediate and smooth implementation are already in place. Its readiness is therefore better described as preparatory rather than implementation-ready. This profile is more consistent with a pilot-first, gradual and closely monitored approach than with a broader or immediate rollout.

5.7 Chapter summary

Chapter 5 examined how ready the company appears to be for the possible use of AI in QC. The analysis first described a QC system that works in practice, but still depends strongly on human judgement, practical experience and mixed paper-and-digital records. This is most visible at incoming inspection, where acceptance, rejection and classification decisions have to be made quickly and under operational pressure.

The participants discussed AI mainly in practical terms. They did not present it as a general digital upgrade, but as possible support for receiving, classification, monitoring, traceability and decision documentation. They associated it with greater speed, consistency and objectivity, but also raised doubts about reliability, usability, practical fit and business value. The analysis of technological, organizational and environmental factors gave a similar picture. The company has useful data, traceability practices and practical know-how, but still faces gaps in data structure, digital integration, AI familiarity, training and implementation planning. External pressure from customers, suppliers, competition and regulatory or market expectations strengthens the case for better QC, without making adoption easier by itself.

The comparison between Management, Production and QC showed broad agreement on the limits of the current system and the possible value of AI, but also different priorities. QC focused on inspection reliability, Production on process fit, and Management on feasibility and return. The company’s readiness can therefore be described as conditional commitment with weaker efficacy. It appears interested in AI-supported QC, but it is not yet implementation-ready. The next chapter discusses these empirical findings in relation to the conceptual framework and the relevant literature.

6 Chapter 6 - Discussion & Interpretation of the Results

6.1 Introduction to the discussion

This chapter discusses the interview findings in relation to the conceptual framework and the relevant literature. It first considers the company's current QC and digital baseline, and then examines how participants understood the value and limits of AI in QC. The chapter then discusses the TOE-related readiness factors, the differences between Management, Production and QC, and the overall readiness profile in terms of change commitment and change efficacy.

6.2 Discussion of the current QC context and digital baseline

In relation to Objective 1 and Research Question 1, which concern the current QC system and the existing digital practices of the case company, the findings show that the company is neither starting from a fully manual environment nor from a mature digital QC environment. There is already a functioning QC system with clear control points, basic traceability practices, and a clear link between incoming inspection and subsequent production and quality decisions. This matters for the present study because any AI-supported QC initiative would have to build on these existing control points, traceability routines and incoming-inspection decisions, rather than enter a blank or purely manual system. In this sense, the case shows an existing operational base, but not yet the level of digital maturity that usually facilitates the smooth integration of AI-supported quality practices.

At the same time, the existing digital baseline remains partial. Chapter 5 showed that relevant data do exist, but much of it remains handwritten or only partly digitalised, while its use is not yet fully systematic. This can be compared with Wilkinson et al. (2016), who link FAIR data to the "ability of machines to automatically find and use the data" and describe FAIR as "Findable, Accessible, Interoperable and Reusable" for both machines and people (pp. 1, 3), and with Mansouri et al. (2021), who frame data quality as "fitness for use" and refer to "accuracy, timeliness, completeness, and reliability" (p. 2). The present findings confirm the relevance of these requirements, but show that the case company's issue is not the absence of

QC or traceability records; rather, it is the gap between existing operational records and data that are sufficiently structured, consistent and reusable for AI-supported decision-making.

A third point concerns the nature of the QC context itself. In this case, the receiving environment remains demanding because of natural raw-material variability, high time pressure, partial visibility inside baskets and practical limits in in-house measurement. This means that AI-readiness is constrained not only by data maturity, but also by the extent to which the receiving process itself can support reliable and repeatable AI-assisted assessment.

Overall, the current QC context and the existing digital baseline indicate an intermediate starting point: more organized than a purely manual setting, but less mature than a fully data-driven Quality 4.0 environment. This helps to explain why participants clearly recognize the potential value of AI in QC, but do not consider that the current situation is sufficient in itself for immediate adoption. In this sense, the case points to the need for further strengthening of the digital and process baseline before any substantial transition to AI-supported QC.

6.3 Discussion of the perceived value and limits of AI in QC

In relation to Objective 2 and Research Question 2, which concern the perceived opportunities, challenges, and potential value of AI in QC, the findings show that the perceived value of AI lies primarily in its expected contribution to incoming inspection, especially through greater objectivity, consistency, and speed. This result is consistent with Liakos et al. (2025), who link ML-based QC with “real-time, non-destructive quality assessment” and “high-throughput visual inspection” for defect detection and classification (p. 2), and with Patel et al. (2012), who describe computer vision as a “rapid, economic, consistent and objective inspection technique” (p. 124). The present findings confirm this potential, but specify it in the company’s receiving stage: AI is valued only if it can improve objectivity, consistency and speed under high time pressure, variable grape leaf characteristics, limited visibility inside baskets, and supplier-facing acceptance or rejection decisions.

The findings also show that the perceived value of AI is not limited to inspection, but extends to monitoring, traceability and broader decision support. This extends the comparison above from visual inspection to broader process-control value. However, in the case of this study, this value remains clearly conditional. Participants do not view AI as an obviously useful solution, but as something that must demonstrate its practical usefulness, reliability and business value within the actual conditions of the company.

This is particularly important in relation to the limits highlighted by the findings. The literature presents solutions such as computer vision, machine vision and related AI applications as powerful tools for food quality assessment, but the case shows that their usefulness depends on the actual setting in which they are expected to operate. In the company under consideration, the receiving environment is characterized by natural and variable raw material, partial visibility, high time pressure and practical constraints in measurement and handling. Therefore, the discussion is not only about what AI can do in principle, but whether it can operate reliably and with clear practical benefit in the specific operational conditions. In this sense, the case does not reject the value of AI in QC, but shows that this value directly depends on the practical fit of the technology with the actual inspection environment.

6.4 Discussion of organizational readiness factors through the TOE lens

In relation to Objective 3 and Research Question 3, which concern the key factors shaping organizational readiness for potential adoption of AI in QC, the findings can be discussed through the TOE lens. In the conceptual framework, the TOE functions as the independent framework of determinants, while organizational readiness is the dependent outcome. Specifically, Technology refers to the quality and standardization of QC data and the technical capability to collect and organize data that AI requires to support the receiving flow; Organization refers to the internal standardization of processes, the allocation of roles/responsibilities, and the organizational capabilities for consistent QC execution and recording; and Environment refers to the external requirements that drive documentation and traceability. Accordingly, H1 concerns the degree of structured/standardized processes and data in incoming inspection, H2 the strength of management support and the adequacy of resources/capabilities for change, and H3 the intensity of external requirements for traceability/compliance and quality documentation.

From a technological perspective, the interviews support the importance of H1. The conceptual framework assumes that readiness for AI-enabled QC is linked to sufficiently structured processes and data in incoming inspection. In the empirical material, this appears in the form of an existing but partial data basis: mixed paper-and-digital recording, partial digital integration, and practical limits in visibility and in-house measurement. This result is consistent with Jöhnk et al. (2021), who note that AI-based systems are more precise when processes are structured and provide standardized data input, while data quality supports accurate AI outcomes (p. 11). It also aligns with Issa et al. (2022), who stress that AI implementation requires robust technological infrastructure and the conversion of raw data into a usable strategic asset (pp. 35–36). The present findings confirm these points in the case company: QC and traceability data exist, but they are not yet sufficiently standardized, connected and operationally usable for AI-supported incoming inspection.

The point is not that the company lacks traceability, batch records or QC-related data. Rather, the findings indicate that these elements already exist, but were not formally assessed in this study against FAIR principles or CTE/KDE-based traceability standards. These concepts are therefore used as analytical reference points for data governance and AI-readiness, not as formal compliance criteria.

From an organizational perspective, the interviews clearly support the importance of H2. At the conceptual level, this is consistent with Weiner's (2009) view that change efficacy depends on the appraisal of "task demands, resource availability, and situational factors" (p. 4), and with Jöhnk et al. (2021), who link AI readiness to top management support and upskilling (p. 11). It also corresponds with Badghish and Soomro's (2024) finding that sustainable human capital had a significant effect on AI adoption, while organizational support did not (p. 14). In the present case, this distinction is important: general support for AI exists, but readiness depends on whether this support becomes clear ownership, training, cross-functional coordination and continuity of knowledge across seasons. Thus, the findings show that readiness does not depend only on the potential usefulness of the technology, but also on whether the company has the people, time, routines and internal support structure that adoption requires in practice. This provides strong support for H2.

From an environmental perspective, the findings also support the importance of H3. In the conceptual framework, the environmental dimension concerns external requirements that push towards traceability, compliance and documented quality data flows, while H3 posits that the intensity of these requirements is related to readiness for AI-enabled QC. This is consistent with GS1 (2017), which identifies "market pressures and emerging regulations" as "critical drivers of traceability" (p. 9), and with FAO (2017), which states that traceability requires linking "the physical flow of products with the flow of information about those products" (p. 7). In the present case, this appears through customer demands for stable quality and traceability, competitive pressure, and the sensitivity of supplier-facing decisions at the receiving stage. Therefore, H3 is supported, but mainly as a driver of perceived need and change commitment rather than as direct evidence that the company already has the internal capacity for AI-enabled QC adoption.

Overall, the discussion through the TOE lens shows a clear correspondence between the conceptual framework and the interview material. H1–H3 are supported, but not with the same weight: H1 is supported with clear technological limitations, H2 is supported particularly strongly, and H3 shows that external pressures reinforce the need for improvement in QC. This picture provides the basis for the following sections, which consider the cross-role interpretation of the findings and, subsequently, the company's readiness through the two core dimensions of change commitment and change efficacy.

6.5 Discussion of cross-role convergence and divergence

In relation to Objective 3 and Research Question 3, the cross-role interpretation is important because Weiner (2009) treats organizational readiness as a "shared psychological state", based on members' "shared resolve" to implement change and their "shared belief" in collective capability (p. 1). From this perspective, convergence and divergence between Management, Production and Quality Control are not only descriptive differences between interview groups, but evidence of how far readiness is shared across functions. The cross-role comparison is also consistent with the methodological logic of the study, as comparison across functions has already been used as part of the trustworthiness strategy.

In this light, the convergence highlighted in Chapter 5 has special weight. The fact that all three groups recognize incoming inspection as the most critical point of the current QC system, that they see the current environment as strongly human-dependent, and that they attribute potential value to AI in QC mainly through objectivity, consistency and speed, shows that there is a shared diagnostic understanding of the problem and the possible direction of change. This does not in itself mean high readiness, but it is consistent with the existence of a shared understanding of why change may be worthwhile. In this sense, the cross-role findings reinforce the interpretation of conditional change commitment that already emerged in 5.6.

In contrast, divergence more clearly illuminates weaker change efficacy. QC emphasizes the practical fit of the technology within the actual conditions of the receiving environment. Production shifts the focus to the practical adaptation of the technology within the broader process flow. Management focuses more on feasibility, value for money, pilot logic, and a credible implementation path. This divergence does not negate the recognition of the potential value of AI, but it shows that confidence regarding how adoption could be successfully implemented is not equally distributed across roles. This shows that the company's readiness is not fragmented in terms of problem recognition, but remains uneven in terms of shared belief in implementation capacity. In this sense, the cross-role findings are fully compatible with the overall profile of conditional commitment but weaker efficacy that already emerged from Chapter 5.

6.6 Discussion of change commitment and change efficacy

In relation to Objective 3 and Research Question 3, the discussion can now move from the TOE factors to the readiness outcome of the study, namely change commitment and change efficacy. This distinction directly follows Weiner (2009), who defines organizational readiness through members' "shared resolve to implement a change" and their "shared belief in their collective capability to do so" (p. 1), while also linking change efficacy to "task demands, resource availability, and situational factors" (p. 4). In the present case, this distinction is critical: the company shows conditional commitment to AI-supported QC, but weaker efficacy regarding its immediate implementation.

Participants recognized the limits of the current QC system and connected AI with possible improvements in objectivity, consistency, speed, monitoring and decision support. This is close to Weiner's view that commitment is stronger when a change is considered worthwhile. However, the case does not show unconditional commitment. AI was not accepted simply as a desirable technology. It was judged against practical usefulness, reliability and business value.

The company therefore appears willing to consider AI, but only if the technology can prove its value in the actual QC environment.

The picture is weaker when it comes to change efficacy. In Weiner's framework, efficacy depends on whether members believe they can organize and carry out the actions required for change, taking into account task demands, resource availability and situational conditions. In this case, all three create difficulties. The task demands are high because receiving takes place under time pressure, with variable raw material and demanding inspection conditions. Resources are also limited by partial digitalisation, handwritten records, measurement limits, training needs and seasonal staffing discontinuity. The situation itself adds another constraint, since participants still questioned whether AI could fit the real inspection environment. As a result, the case shows willingness to consider AI, but not an equally strong shared belief that the company can already implement it effectively.

Overall, the discussion through the two readiness dimensions shows that the case is characterized by conditional change commitment but weaker change efficacy. This is fully consistent with the conceptual model of the study: the TOE factors function as determinants, but readiness is ultimately judged by whether these determinants translate into collective intention and collective confidence for implementation. In the company under consideration, the former appears present but conditional, while the latter remains clearly weaker.

This discussion provides the basis for the general conclusions, managerial implications, and practical recommendations presented in the next chapter.

7 Chapter 7 - Summary & Conclusions

7.1 Overview of the study

This study investigated organizational readiness for the potential adoption of AI in QC in a grape leaf processing company, with particular emphasis on incoming inspection as a critical point of the current QC system. The research followed a qualitative single-case study approach and was based on six semi-structured interviews with participants from Management, Production and Quality Control, who were selected as information-rich informants in order to capture different functional perspectives, including some variation across company units and QC shifts. Through thematic analysis and guided by the study's conceptual framework, the research examined the current QC context, the perceived value and limitations of AI in QC, as well as the key factors shaping the company's readiness for such a change. While RQ1–RQ3 were addressed directly through the thematic analysis of the interview material, RQ4 is addressed synthetically in this chapter. More specifically, the conclusions and practical recommendations translate the empirical findings into a gradual readiness-strengthening and AI integration logic for the company's QC system.

7.2 General conclusions

Overall, the case company cannot be described as either ready or unwilling to adopt AI in QC. The interviews show a more cautious position. AI is seen as relevant, especially for incoming inspection, where decisions have to be made quickly and with consistency. However, this interest is not matched by full confidence in the company's current ability to implement such a change. The company appears to have stronger change commitment than change efficacy: it can see why AI-supported QC may be useful, but the practical conditions for adoption are still incomplete. These conditions mainly concern data structure, staff continuity, training, process fit and the ability to test the technology under real receiving conditions. The case therefore points to an intermediate readiness stage, where AI is considered worthwhile, but immediate implementation would be premature.

7.3 Managerial implications

For management, the main implication is practical: AI in QC should not be approached as a standalone technological investment. In this company, any meaningful AI initiative would need to start from incoming inspection, because this is where operational pressure, supplier-facing decisions and quality risk come together. Management should therefore treat receiving as the first priority area, not because it is the only possible use of AI, but because it is the point where the current weaknesses and potential benefits are most visible. The value of AI will depend not only on the technical performance of the system, but also on whether the company prepares the conditions around it: more consistent data, clearer receiving routines, coordination between Management, Production and QC, and clear ownership of the pilot. The managerial issue is therefore not simply whether AI could help, but whether the company can integrate it into a controlled and realistic change process.

A second implication concerns people, training and cost exposure during any pilot phase. Management would need to balance the need for technical expertise with the uncertainty that normally comes with a first AI initiative. Since the company operates under strong seasonality, the staffing model should avoid creating heavy fixed commitments before the usefulness of the system is tested. It would be more realistic to rely first on selected existing staff, supported where necessary by external technical expertise, and to focus training on the people who would actually use or validate the system during receiving. This also matters for knowledge continuity, since seasonal staffing can make it difficult to retain skills from one production period to the next.

Finally, management would need to consider how AI-supported decisions affect supplier-facing relationships. Incoming inspection is not only an internal QC step; it also influences acceptance, rejection, payment and the perceived fairness of the process. Greater objectivity and consistency could strengthen trust in the inspection process, but only if AI-supported decisions remain understandable, reviewable and under human oversight. For this reason, the managerial challenge is to evaluate efficiency, reliability, cost, staff continuity and supplier-facing credibility together, rather than treating AI adoption as a purely technical improvement.

7.4 Practical recommendations for the case company

The recommendations below draw on the empirical findings of the study and the readiness logic of the conceptual framework. They are adapted to the operating conditions of the case company and focus on practical steps for strengthening readiness and testing AI-supported QC in a controlled way.

1. **Start with a pilot at incoming inspection.**

   Incoming inspection should be the first area for testing AI-supported QC. It is where time pressure, human judgement, quality risk and supplier-facing decisions come together most clearly. Testing AI at this stage would show whether it can improve consistency and documentation without disrupting the receiving flow.

2. **Use the central unit of the subsidiary as the initial pilot setting.**

   The first pilot should take place in the central unit of the Chinese subsidiary. Compared with the other units, this setting offers closer day-to-day coordination, stronger management involvement and better staffing support. Since readiness is still uneven, the first test should be placed where monitoring and corrective action can be managed more easily.

3. **Strengthen receiving and QC data before and during the pilot.**

   AI-supported QC would require more consistent and usable data than the company currently has. Before expecting AI to work reliably, the company should improve the structure of receiving and QC records, reduce the gap between handwritten and digital data, and make sure that inspection results are clearly linked to batches, suppliers and acceptance or rejection decisions. This does not require a complex data system from the start; it requires existing records to become more consistent and easier to use.

4. **Assign clear operational ownership and a small cross-functional pilot team.**

   The pilot should have one clearly responsible operational owner and a small working team involving Management, Production and QC. This is needed because the interviews showed shared interest in AI, but not the same confidence about implementation. A small cross-functional team would keep the pilot close to the real receiving process, connect technical choices with daily operating conditions, and make sure that problems are followed up rather than left as general observations.

5. **Align staffing, training and pilot timing with seasonality.**

The pilot should be designed around the company's seasonal operating reality. Heavy staffing commitments should be avoided before the usefulness of the system has been tested. A more realistic approach would be to train selected existing staff, with external technical support where needed, and to schedule training close to the production period so that knowledge is used while it is still fresh. The company should also keep simple records of what is learned during the pilot, so that this knowledge can be carried into the next season.

6. **Keep human oversight and expand only after validation.**

During the pilot, AI should support decisions rather than replace human judgement. This matters especially at receiving, because decisions affect supplier relations, acceptance or rejection of leaves, and perceptions of fairness. Any AI-supported classification should remain reviewable and understandable for the people responsible for QC. Expansion to other stages should be considered only if the pilot performs reliably under real receiving conditions, creates clear operational value, remains acceptable in terms of cost and does not weaken supplier-facing credibility.

Table 1 summarizes the recommendations, their empirical basis and their practical meaning for the company.

Recommendation	**Empirical / readiness basis**	**Practical implication**
Pilot AI at incoming inspection.	Highest pressure point; strong dependence on human judgment.	Start with a limited and controlled pilot at receiving.

Use the central unit first.	Stronger coordination and closer management presence.	Test the pilot in the most manageable setting.
Strengthen QC data structure.	Mixed paper/digital records and partial digitalisation.	Standardize QC records and batch-linked data.
Assign clear ownership.	Readiness depends on responsibility and coordination.	Create a small Management–Production–QC pilot team.
Align training with seasonality.	Seasonal staffing weakens continuity and change efficacy.	Train selected staff and retain knowledge across seasons.
Keep human oversight.	Supplier-facing decisions require fairness and credibility.	Use AI as decision support, not final autonomous judgment.

Table 1 Summary of practical recommendations for strengthening AI readiness in QC

7.5 Limitations of the study

The findings should be interpreted in light of several limitations. The study is based on a qualitative single-case design, which allowed a detailed examination of the company context but does not support statistical generalization to other agri-food SMEs. The empirical material also comes from six internal participants from Management, Production and Quality Control, so the perspectives of other relevant actors, such as leaf suppliers or customers, were not included. Access to participants depended on availability and workload, which may have affected the timing and breadth of data collection. Part of the empirical material was also based on retrospective descriptions of the 2025 production season, meaning that certain details may have been less immediate than they would have been during live observation. In addition, the interviews were documented through detailed notes rather than audio recording, which may have reduced the amount of exact verbal detail available for analysis. Finally, the study examines organizational readiness for the possible adoption of AI in QC, rather than the implementation or measured performance of a specific AI system in practice.

7.6 Suggestions for future research

Given that this study focused on organizational readiness for the potential adoption of AI in QC in a single case company, future research could move in the following directions:

- Comparative or multi-case research in similar agri-food companies, in order to examine whether the present findings have broader relevance across other organizational environments.
- Investigation of the actual implementation of a pilot AI in QC application, and not only readiness, in order to empirically assess how change commitment and change efficacy change in practice.
- Longitudinal research, in order to examine how readiness evolves before, during and after a potential pilot or implementation phase.
- Inclusion of the perspectives of other stakeholders, especially leaf suppliers, whose relationships with the company are directly affected by incoming inspection decisions.
- More systematic investigation of the role of seasonality in issues such as training, knowledge retention, staffing stability and the long-term feasibility of adopting AI-supported QC systems.
- Cross-unit comparison between the central unit and the two other units of the subsidiary, in order to examine whether different operational conditions shape organizational readiness in different ways.
- Combination of qualitative findings with more structured operational data, through mixed-method approaches, in order to examine more systematically the relationship between perceptions, process conditions and implementation outcomes.
- Future research could also conduct a bibliometric review of AI readiness and AI adoption in agri-food SMEs, in order to map the evolution of the field, dominant research themes, influential publications and remaining under-researched areas.

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Appendix A: Semi-Structured Interview Guide

This appendix presents the semi-structured interview guide used in the study. To preserve the analytical design logic of the instrument, the guide is presented together with indicative probes, the immediate purpose of each question, the related conceptual factor(s), the readiness lens, and the linked Objective(s), Research Question(s), and Hypothesis/Hypotheses where applicable.

Question numbering follows the original design logic of the guide: Common Core (1–7), QC add-on (1.1–1.5), Production add-on (2.1–2.4), and Management add-on (3.1–3.10).

A.1 Common Core

No.	Main Question	Probes & Expected Response Themes	Goal / aim (Why)	Citation(s) (author, page)	Conceptual factor(s)	Readiness lens	Linked objective / RQ / H
1	Could you describe your role and responsibilities in the organization?	Main day-to-day responsibilities? Involvement in QC / receiving / production?	Define respondent role/perspective.	Aryal & Chukro (2025), p. 59	O	N/A	Obj1;RQ1
2	In your role, what types of decisions do you make that relate to quality, receiving, or production?	Acceptance/rejection? classification? flow decisions? escalation?	Map decision context for cross-role comparison.	Entzenberg & Söderqvist (2020), p. 51	O	N/A	Obj1;RQ1
3	What do you think AI could do in your area of work?	Where exactly could it help? Which tasks or decisions?	Elicit perceived usefulness by function.	Aryal & Chukro (2025), p. 59	T/O	Commitment	Obj2;RQ2

No.	Main Question	Probes & Expected Response Themes	Goal / aim (Why)	Citation(s) (author, page)	Conceptual factor(s)	Readiness lens	Linked objective / RQ / H
4	What internal factors are making the company consider AI?	Subjectivity in QC? fatigue? speed of receiving? raw-material variability? dependence on experienced staff?	Identify internal drivers / pain points.	Aryal & Chukro (2025), p. 60	O	BOTH	Obj2;RQ2;Obj3;RQ3;H2
5	What external factors are making the company consider AI?	Customers? market? traceability? compliance? competitors? regulation?	Identify external drivers / pressures.	Aryal & Chukro (2025), p. 60; Gupta & Ljunggren (2025), p.43; Entzenberg & Söderqvist (2020), p. 52	E	N/A	Obj2;RQ2;Obj3;RQ3;H3
6	What could prevent AI adoption from being successful in this company?	Poor data? low trust? unclear pilot? limited skills? no owner? flow disruption?	Identify primary blockers at company level.	Aryal & Chukro (2025), p. 61	T/O/E	BOTH	Obj2;RQ2;Obj3;RQ3;H1;H2;H3
7	How ready do you think your area is for the change required by AI, and what support would be needed?	Training? clearer roles? pilot before rollout? management support? cross-functional coordination?	Assess local readiness and support needs.	Aryal & Chukro (2025), p. 61	O	Both	Obj3;RQ3;H2

Table 2 Common Core Interview Guide Matrix

A.2 QC add-on

No.	Main Question	Probes & Expected Response Themes	Goal / aim (Why)	Citation(s) (author, page)	Conceptual factor(s)	Readiness lens	Linked objective / RQ / H
1.1	In your QC role, what types of quality decisions do you make (e.g., release, rejection, classification)?	What is the impact of those decisions on batch quality, cost, or flow?	Map QC decision points.	Entzenberg & Söderqvist (2020), p. 51	O	N/A	Obj1;RQ1

No.	Main Question	Probes & Expected Response Themes	Goal / aim (Why)	Citation(s) (author, page)	Conceptual factor(s)	Readiness lens	Linked objective / RQ / H
1.2	What data do you rely on to make these QC decisions, and what data is missing?	Grades? Defect notes? Photos? Batch IDs? Supplier info? Measurement data? What is often missing?	Identify decision-critical QC data and gaps.	Entzenberg & Söderqvist (2020), pp. 51–52	T	N/A	Obj1;RQ1;H1
1.3	How do you currently manage QC-related data and records?	Paper? Excel? ERP? Photos? Who records them? How standardized are fields and codes? Are they linked to batch IDs?	Assess QC data/records handling maturity.	Entzenberg & Söderqvist (2020), p. 52	T/O	N/A	Obj1;RQ1;H1
1.4	If AI is introduced in QC, how would it change your decision-making process?	Speed? Consistency? Trust? Human override? Accountability?	Assess perceived AI impact on QC decision process.	Entzenberg & Söderqvist (2020), p. 52	O	Both	Obj2;RQ2
1.5	What could prevent AI adoption from being successful in quality control, especially during incoming inspection and batch decisions?	Wrong decisions? Low trust? Poor data? Slow flow? Unclear criteria?	Elicit QC-specific blockers (if not already covered in C6).	Aryal & Chukro (2025), p. 61	T/O	BOTH	Obj2;RQ2;Obj3;RQ3;H1;H2

Table 3 QC Add-on Interview Guide Matrix

A.3 Production add-on

No.	Main Question	Probes & Expected Response Themes	Goal / aim (Why)	Citation(s) (author, page)	Conceptual factor(s)	Readiness lens	Linked objective / RQ / H
2.1	What type of data is stored in the current systems that could be relevant to production and quality decisions?	Batch data? Receiving times? Line conditions? Production logs? Rework data? Supplier/batch linkage?	Identify usable production-side data.	Gupta & Ljunggren (2025), p. 43	T	N/A	Obj1;RQ1;H1
2.2	What technological or operational barriers could make AI difficult to use in production operations?	Integration? Time pressure? Flow disruption? Seasonality? Unclear rules? Practical fit?	Capture production-side barriers.	Gupta & Ljunggren (2025), p. 43	T/O	Efficacy	Obj2;RQ2;Obj3;RQ3;H1;H2
2.3	If AI were introduced, how could it affect the production and receiving flow?	Speed up? Create bottlenecks? Improve handoff to QC? Add extra checks? Influence rework/holds?	Assess operational impact on flow.	Entzenberg & Söderqvist (2020), p. 52 (adapted)	O	Both	Obj2;RQ2
2.4	What obstacles influence the adoption of AI in production-related decision-making, and to what extent?	Flow pressure? Unclear decision authority? Fit with receiving realities? Coordination with QC?	Elicit production-side obstacles (optional deepening).	Entzenberg & Söderqvist (2020), p. 52 (adapted)	O	Efficacy	Obj3;RQ3;H2

Table 4 Production Add-on Interview Guide Matrix

A.4 Management add-on

No.	Main Question	Probes & Expected Response Themes	Goal / aim (Why)	Citation(s) (author, page)	Conceptual factor(s)	Readiness lens	Linked objective / RQ / H
3.1	What are the main reasons why your company has not yet engaged more actively	Why not yet? What has held the company back so far?	Elicit reasons for limited AI engagement so far.	Aarstad & Saidl (2019), p. 96	T/O/E	BOTH	Obj2;RQ2;Obj3;RQ3;H1;H2;H3

No.	Main Question	Probes & Expected Response Themes	Goal / aim (Why)	Citation(s) (author, page)	Conceptual factor(s)	Readiness lens	Linked objective / RQ / H
	in considering AI for incoming quality control of grape leaves?						
3.2	If the company were to consider AI for QC, where should it start and what could be a good first use case?	Incoming inspection? visual grading? defect detection? batch prioritization? traceability support?	Define a plausible starting point and first use case.	Kopra (2025), p. 63	T/O	Commitment	Obj2;RQ2;Obj4;RQ4
3.3	What business objectives should a possible AI initiative in QC pursue, and based on which criteria should management prioritize the first use case or pilot?	Consistency? speed? traceability? waste reduction? business value? feasibility? data readiness? pilot measurability?	Link AI to objectives, goal-setting, and prioritization in one cluster.	Kopra (2025), p. 63; Kopra (2025), p. 64; Aarstad & Saidl (2019), p. 94	T/O	Both	Obj4;RQ4
3.4	How should a possible AI-for-QC initiative be aligned with the company's broader strategy and operational priorities?	Seasonal realities? quality strategy? production priorities? customer requirements? competitor pressure?	Assess strategic alignment.	Kopra (2025), p. 63; Gupta & Ljunggren (2025), p. 43	O	Commitment	Obj4;RQ4;H2
3.5	What aspects of data handling do you see as most important if the company were to consider AI in QC?	Data quality? availability? standardization? batch linkage? ownership? access? enough past/current records?	Define data prerequisites for AI-enabled QC.	Kopra (2025), p. 64	T	Efficacy	Obj3;RQ3;H1
3.6	Are there any resource constraints that would affect an investment in AI for QC?	Budget? time? people? vendor support? pilot window? competing priorities?	Assess investment feasibility via resources.	Aarstad & Saidl (2019), p. 94	O	Efficacy	Obj3;RQ3;H2
3.7	What risks do you see when thinking about AI adoption in this company, and are any of them too high to justify moving forward?	Wrong accept/reject? slow receiving? poor fit with variable raw material? data problems? vendor dependence? unacceptable risks?	Map risk landscape and red lines.	Aarstad & Saidl (2019), p. 95	T/O/E	BOTH	Obj2;RQ2;Obj3;RQ3;H1;H2;H3

No.	Main Question	Probes & Expected Response Themes	Goal / aim (Why)	Citation(s) (author, page)	Conceptual factor(s)	Readiness lens	Linked objective / RQ / H
3.8	If the company were to consider AI for QC, do you think employees would see it more as a helpful tool or as a threat to their jobs? Why, and where would you expect the strongest resistance?	Middle managers? supervisors? front-line employees? skills fears? role ambiguity?	Assess anticipated employee perceptions and resistance points.	Gupta & Ljunggren (2025), p. 43	O	Commitment	Obj3;RQ3;H2
3.9	How ready is the company, as an organization, for the change required by AI adoption in QC, and what managerial practices would be necessary to support this change?	Training? communication? role clarity? pilot-before-scale? management support? people-and-skills approach?	Assess organizational readiness and managerial practices.	Aryal & Chukro (2025), p. 61; Kopra (2025), p. 64	O	Both	Obj3;RQ3;Obj4;RQ4;H2
3.10	What kind of working group should the company use to shape a possible AI strategy or pilot for QC, and how should this group prepare and support employees through the change process?	Who should be included? QC? production? management? external partner? who owns decisions? how will staff be supported?	Define ownership structure + change-support design.	Kopra (2025), p.63; Aryal & Chukro (2025), p.61	O	BOTH	Obj4;RQ4;H2

Table 5 Management Add-on Interview Guide Matrix

Legend for abbreviations used in the guide

- Obj1 = Describe the existing quality control system and the current use of data and digital tools in the company.
- Obj2 = Explore how key organizational members perceive the opportunities and challenges of AI in quality control.
- Obj3 = Analyze which organizational characteristics enhance or limit readiness to adopt AI in quality control.
- Obj4 = Synthesize proposals for the gradual integration of AI tools into the company's quality management system.
- RQ1 = How is quality control currently organized in the company, and what is the role of data and digital tools in its operation?

- RQ2 = How do executives and other key organizational members perceive the opportunities and challenges of AI in quality control?
- RQ3 = Which organizational factors enhance or limit the company's readiness to adopt AI in quality control?
- RQ4 = Based on the empirical findings, how can the company gradually strengthen its readiness and integrate AI tools into its quality management system?
- H1 (Technology) = The degree of structured/standardized processes and data in incoming inspection is related to the organizational readiness for implementing AI-enabled QC in the grape leaf processing unit.
- H2 (Organization) = The strength of management support and the adequacy of resources/capabilities for change (e.g. time, human resources, QC–IT–production skills) are related to organizational readiness for implementing AI-enabled QC in incoming inspection.
- H3 (Environment) = The intensity of external requirements for traceability/compliance and quality documentation is related to organizational readiness to implement AI-enabled QC in incoming inspection in the grape leaf processing unit.
- Conceptual factor(s): T = Technology; O = Organization; E = Environment.
- Readiness lens: Commitment; Efficacy; Both; N/A

Appendix B: Participant Information Sheet and Consent Form

B.1 Participant Information Sheet

Researcher

Marios Lygkonis

MBA Dissertation, Hellenic Open University

Title of study

Understanding Organizational Readiness for AI in Quality Control: A Case Study in Grape Leaf Processing through Stakeholder Interviews

Research purpose

The study examines how the company's organizational readiness is shaped for the possible adoption of AI-enabled tools in quality control, with an emphasis on the incoming inspection / receiving stage.

Why you are invited

You are participating because your role is directly related to quality control, production, management, or related decision-making and organizational preparation processes.

What participation involves

Participation involves a semi-structured interview of approximately 40–60 minutes. The discussion focuses on current practices, perceptions of potential use of AI in QC, and organizational factors that can facilitate or hinder it.

Voluntary participation

Participation is completely voluntary. You can refuse to answer any question or stop the interview at any time without any repercussions.

Recording

The interview will only be recorded if you give your explicit consent. If you do not agree, only detailed notes will be taken.

Confidentiality / anonymity

The data will be used for academic purposes only. Any transcripts/notes will be anonymized with pseudonyms or codes, without direct identifiers. Consent forms will be kept separate from the main research data body.

Data handling

The audio files, notes and transcripts will be stored in a secure personal environment with limited access and only for the necessary period of the research.

Questions / Contact

If you have questions about the study or your participation, you may contact:

Marios LYGKONIS/ lygkonis.marios@gmail.com / +86 15109950975

B.2 Short Oral Opening Script Used Before Each Interview

Thank you for taking part in this interview. I am conducting this interview as part of my MBA dissertation on organizational readiness for the possible use of AI-enabled tools in quality control in a grape leaf processing company.

The interview is about current practices, possible future use of AI in incoming inspection, and the organizational conditions that may support or hinder such a change. It is not an evaluation of your personal performance.

Your participation is voluntary. You may choose not to answer any question, and you may stop the interview at any time.

With your permission, I would like to audio-record the interview for accuracy. If you prefer not to be recorded, I will only take detailed notes.

All information will be treated confidentially and anonymized.

Do you have any questions before we begin? And do I have your permission to record the interview?”

B.3 Consent Form

Consent to Participate in the Study

Study Title:
Understanding Organizational Readiness for AI in Quality Control: A Case Study in Grape Leaf Processing through Stakeholder Interviews

Please read the statements below and indicate your agreement.

I confirm that:

[ ] I have read and understood the Participant Information Sheet.
[ ] I have had the opportunity to ask questions about the study.
[ ] I understand that my participation is voluntary.
[ ] I understand that I may refuse to answer any question.
[ ] I understand that I may withdraw from the interview at any time before its completion, without negative consequence.
[ ] I understand that the interview data will be used only for academic research purposes.
[ ] I understand that my responses will be anonymized and treated confidentially.
[ ] I understand that no directly identifying information will be included in the dissertation.
[ ] I understand that consent forms will be stored separately from transcripts and notes.
[ ] I agree to participate in this interview.

Audio recording
Please select one:

[ ] I agree to audio recording of the interview.
[ ] I do not agree to audio recording of the interview. I understand that detailed notes will be taken instead.

Participant Name: ____________________
Signature: ____________________
Date: ____________________

Researcher Name: Marios LYGKONIS

Signature: ____________________

Date: ____________________

Appendix C: Concise Data Management Plan

This study uses qualitative interview data collected for academic research purposes only. In practice, the interviews were documented through detailed written notes, as no participant consented to audio recording. The research data therefore consist of interview notes, anonymised written records, and analysis files such as coding tables and thematic notes. This also appeared to be more consistent with participants' preference for a less formal interview setting within the particular interpersonal and cultural context of the study.

All research data were stored in the researcher's secure personal digital environment with restricted access. Access to the data was limited to the researcher only. Since no interviews were audio-recorded, no audio files were created or stored.

To protect confidentiality, all interview material was anonymised, and any identifying details were excluded from the analytical material. Consent forms were stored separately from the main research data corpus.

The data will be retained only for the period necessary for the completion and examination of the dissertation. After that period, the interview notes, anonymised records, and related working files will be securely deleted, while only the final dissertation text will remain as the formal academic output of the study.

Appendix D: Illustrative Codebook Extract and Coding Trail

This appendix provides an illustrative extract from the study's codebook and coding trail. It is included to enhance analytical transparency by showing how selected data fragments were coded and progressively linked to broader sub-themes and themes during the thematic analysis. In line with the methodology of the study, the extract reflects the hybrid coding logic adopted, combining deductive codes linked to the conceptual framework with inductive codes emerging from the interview material.

Illustrative excerpt / data fragment	Initial code	Type of code	Sub-theme	Main theme	Indicative participant group(s)
"Everything has to be done very fast." (QC2)	Time pressure at reception	Inductive	Operational pressure during incoming inspection	Current QC system and digital practices	QC
"Mainly on experience." (PR1); "experience is the key factor." (QC2)	Human-dependent quality decisions	Inductive	Experience-based evaluation practices	Current QC system and digital practices	PR, QC
"Most of it is still paper-based." (QC2); "Most of this data is handwritten." (PR1)	Mixed paper-and-digital recording	Inductive	Fragmented recording practices	Current QC system and digital practices	PR, QC
"We need more objectivity." (QC1); "more objective decision making" (PR2)	Need for objectivity and consistency	Hybrid	AI as quality decision support	Perceived opportunities and challenges of AI in QC	PR, QC
"If we could make the process fast, accurate and consistent…" (QC2)	AI for faster and more accurate inspection	Hybrid	AI-supported incoming inspection	Perceived opportunities and challenges of AI in QC	QC
"My question is how this technology could properly scan the whole surface of the leaf…" (QC2)	Uncertain practical fit of the technology	Inductive	Practical fit as adoption condition	Perceived opportunities and challenges of AI in QC	QC
"training, a clear guidance, baby steps and gradual shifting…" (PR1)	Training and gradual adaptation	Deductive	Conditions for gradual adoption	Organizational readiness factors	PR

Illustrative excerpt / data fragment	Initial code	Type of code	Sub-theme	Main theme	Indicative participant group(s)
“Who guarantees that the same people will be hired?” (QC1)	Seasonal staffing discontinuity	Inductive	Workforce continuity constraints	Organizational readiness factors	QC
“The company seems to recognize the potential value of AI, but … does not yet show a sufficiently strong belief…” (analytic synthesis)	Conditional commitment / weaker efficacy	Deductive	Integrated readiness profile	Integrated readiness profile of the case company	MG, PR, QC

Table 6 Illustrative Codebook Extract and Coding Trail

Appendix E: SRQR

This appendix provides the SRQR reporting checklists for the present study.

No.	Checklist item	Reported on page No(s).
1	Title	Cover Page
2	Abstract	v
3	Problem formulation	1–5, 28
4	Purpose or research question	6–7
5	Qualitative approach and research paradigm	36-39
6	Researcher characteristics and reflexivity	43, Appendix B p. 84, Appendix C p. 85
7	Context	7–8, 37–40, 45-48
8	Sampling strategy	40-41, 44
9	Ethical issues pertaining to human subjects	43, Appendix B pp. 81-85, Appendix C p. 85
10	Data collection methods	39-40, Appendix A pp. 75–80, Appendix B pp. 81–85
11	Data collection instruments and technologies	39–40, Appendix A pp. 75–80, Appendix B p. 85
12	Units of study	37–41, 44
13	Data processing	40, 42–43, Appendix C p. 85
14	Data analysis	42–43, 44–53, Appendix D p. 86
15	Techniques to enhance trustworthiness	42–43, Appendix D p. 86
16	Synthesis and interpretation	54–66
17	Links to empirical data	44–53, Appendix D p. 86

No.	Checklist item	Reported on page No(s).
18	Integration with prior work, implications, transferability, and contribution(s) to the field	54–66
19	Limitations	7–8, 38, 65

Table 7 SRQR Checklist

Author's Statement:

I hereby expressly declare that, according to the article 8 of Law 1559/1986, this dissertation is solely the product of my personal work, does not infringe any intellectual property, personality and personal data rights of third parties, does not contain works/contributions from third parties for which the permission of the authors/beneficiaries is required, is not the product of partial or total plagiarism, and that the sources used are limited to the literature references alone and meet the rules of scientific citations.