



Multi-criteria selection of image acquisition technologies for automatic optical inspection in assembly lines

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Abstract

Ensuring product conformity in industrial assembly lines is becoming increasingly complex due to high production rates, as well as the growing complexity and customisation of products. Zero-Defect Manufacturing (ZDM) aims to eliminate production defects by integrating advanced quality assurance technologies, thereby enhancing processes efficiency and sustainability. Automatic Optical Inspection (AOI), powered by Computer Vision (CV), has emerged as a key enabler of ZDM, automating defect detection and enhancing quality control. However, the industrial adoption of AOI systems is still in its early stages, and there is a need for a structured methodology to assess their technical feasibility and select the most suitable image-acquisition technology. This paper proposes a novel multi-criteria decision-making (MCDM) methodology for selecting image-acquisition technologies in AOI systems. The approach integrates Analytic Hierarchy Process (AHP) and the Weighted Sum Model (WSM) to evaluate alternatives based on key factors such as product dimensions, inspection area dispersion, visibility constraints, and system flexibility requirements. The methodology is validated through two real-world case studies in the automotive sector, demonstrating its effectiveness in supporting technology selection and guiding AOI implementation in real production environments.

Keywords Automatic optical inspection · Zero-Defect manufacturing · Computer vision · Industry 5.0 · Image acquisition · Weighted sum model

1 Introduction

In modern manufacturing, the global mission is to improve production processes in terms of both operational efficiency and sustainability [1]. Several authors have focused on the integration of lean and green principles, finding several similarities and suggesting that they are naturally complementary [2]. High quality enables the pursuit of both objectives by reducing waste and resource consumption [3]. Zero-Defect Manufacturing (ZDM) emphasises this concept by “doing things right the first time”, thereby eliminating defects at every production stage [4, 5]. This approach is critical in today’s competitive market, where minimising environmental impact and enhancing customer satisfaction are key objectives. However, in real-world contexts,

reducing the nonconformities generated within production and assembly processes to zero is extremely challenging. As products become increasingly complex and their life cycles shorten, the likelihood of defects during assembly rises, necessitating robust quality assurance tools along the assembly line [6]. For this reason, ZDM advocates implementing defect detection and prediction campaigns to intercept faulty products before they reach the customer, thereby triggering repairs and preventive measures and reducing the overall impact [7].

In this scenario, Non-Destructive Inspection (NDI) technologies have gained prominence as effective solutions for ensuring product quality without causing damage [8]. These techniques enable the measurement of key factors or the analysis of product quality without compromising any of the characteristics required by product design. Compared to destructive inspections, they do not generate scrap, thereby improving environmental sustainability and reducing production costs. The most widely used NDI methods include visual inspection, microscopy, ultrasonic testing, radiography, dye penetration testing, acoustic emission, magnetic

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particle inspection and eddy current testing [9]. Visual inspection relies solely on image-based assessment and therefore involves no physical contact with the inspected item. Typically, it is performed by human operators who are extensively trained on the inspection specifications, ensuring they possess the necessary expertise to verify product conformity solely through observation [10, 11]. Visual inspections are non-value-added activities, which is why their massive use can negatively affect the overall efficiency of the production system. Furthermore, humans are prone to fatigue and variability in quality performance, often resulting in inconsistent visual inspections [12]. In recent times, Artificial Intelligence (AI) has been used across multiple industrial applications to enhance or replace human tasks [13, 14]. The branch of AI that deals with image analysis, known as Computer Vision (CV), is particularly well-suited for visual inspection, as it offers a lean and green solution. In fact, it enables the verification of compliance with quality requirements for 100% of products, thereby avoiding waste and scrap, without impacting system efficiency [15].

1.1 Computer vision in high-quality manufacturing

In recent years, CV has emerged as a fundamental enabler of Industry 4.0, driven by advances in AI and deep learning [16]. CV encompasses a set of algorithms and techniques that enable computational systems to visually interpret the real world as humans do [17]. Computers are then able to identify objects and patterns by processing digital images [18]. The object detection problem can be split into sub-categories that CV deals with: *object classification*, which focuses on determining the presence of objects belonging to a predefined set of classes within an image; *object recognition*, which aims to identify and localise all the objects present in an image; *semantic image segmentation*, which assigns each pixel in an image to a specific semantic class; *object instance segmentation*, which is a more refined version of the former task and aims to distinguish different instances of the same object class [19]. A pivotal moment in the evolution of CV was the introduction of AlexNet by Krizhevsky et al. [20], which revolutionised CNNs and significantly improved image classification and object detection capabilities [17, 19]. The success of AlexNet in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) demonstrated that deep learning models could outperform traditional feature-based methods, paving the way to the widespread deployment of CV-based systems in industrial production. Large datasets consisting of labelled images, e.g., ImageNet and MS COCO, have also played a key role in the advancement of Convolutional Neural Networks (CNNs), expanding the range of training data on which neural networks are trained and drastically improving

their performance [19]. This technology plays a crucial role in industrial applications such as inspection, data collection, tracking and reporting, monitoring worker movements, robotic guidance, and process optimisation [21]. It is primarily adopted in industries that demand high precision and product quality [22]. conducted a comprehensive analysis of CV adoption in the automotive sector, collecting application cases that span the entire supply chain, from part production and press shops to paint shops and final assembly, most of which are still at the prototype stage in laboratory settings.

Automatic Optical Inspection (AOI) is one of the most significant applications of CV in manufacturing. AOI systems utilise high-resolution cameras and advanced image processing algorithms to detect defects, assess product conformity, and ensure compliance with quality standards with minimal human intervention [23]. Operators often require extensive training to inspect products correctly. However, this need conflicts with the high turnover rate typical of the modern industrial landscape, representing one of the major challenges for the industry [24]. Adopting AOI systems can mitigate this issue, significantly reducing the need to train new inspection personnel. Furthermore, human operators are characterised by variable performance influenced by Human Factors [12], whereas AOI systems ensure consistent and standardised performance. In the context of Industry 5.0, human operators should not be entirely replaced but instead supported by technology that assists them in these tasks, enhancing performance and improving overall system efficiency.

From a ZDM perspective, AOI aligns with the pillar of Defect Detection: deploying robust in-line quality control shortens detection latency and limits the downstream propagation of nonconformities. Lowering both false positives and false negatives, and thereby improving precision and recall, leads to a reduction in the escape rate, which refers to the proportion of non-compliant products that reach customers and is a key ZDM metric. Fewer false negatives cut the need for downstream containment, while fewer false positives reduce unnecessary scrap, rework, and line interruptions. Overall, earlier and more accurate detection decreases the Cost of Poor Quality (COPQ) associated with rework and quality loss.

AOI systems can be employed for the following four types of inspection [23]:

- *Inspection of dimensional quality*: ensures that objects meet predefined dimensional tolerances. It includes checks on geometric properties such as dimensions, shape, position, orientation, alignment, roundness and edge features.
- *Inspection of surface quality*: focuses on detecting defects such as scratches, cracks, roughness, and texture

inconsistencies on the product surface. It is widely used in industries such as metalworking and textile manufacturing.

- *Inspection of structural quality*: verifies the correct assembly of components by detecting missing, misaligned, or incorrectly placed parts. It is commonly applied in electronics and mechanical assembly lines.
- *Inspection of operational quality*: assesses whether a product functions correctly, verifying that a specific operation has been performed within the defined manufacturing process standards.

The robustness and versatility of AOI in performing a wide range of inspections make it particularly appealing for manufacturers seeking to enhance quality assurance processes and reduce reliance on manual inspections.

1.2 Problem statement and research objectives

In today's assembly lines, products are becoming increasingly complex and customisable, raising the risk of defects. Consequently, manufacturers involved in product assembly must implement various quality assurance techniques. In this context, CV is a valuable approach to ensure that products meet the intended design standards before reaching the customer [21, 25, 26]. However, despite recent significant advancements in CV, several barriers still hinder the adoption of AOI systems in manufacturing. Lack of understanding of CV, insufficient funding, limited expertise, and mistrust of CV are among the key factors preventing companies from adopting these solutions [27, 28].

Indeed, investments in AOI systems are often substantial, while assessing their economic return and integration within the production system remains challenging. Several studies in the literature aim to help companies assess the feasibility of such investments [25, 29, 30]. However, no existing studies provide guidance on selecting the technological solution that best fits a specific application. This paper addresses this gap by proposing a novel methodology to support the integration of AOI systems in industry. It introduces an MCDM approach that combines AHP and WSM to guide the selection of the most suitable image-acquisition technology for real-world applications. The choice of image-acquisition technology is particularly relevant, as it directly impacts the operational feasibility of AOI implementation. Each technological alternative has specific advantages and limitations in terms of cost, adaptability, acquisition time, consistency, and scalability. Therefore, selecting the most appropriate solution is a critical step that determines whether and how the system can be applied and integrated on the shop floor. In contrast to performance-centric contributions that optimise AOI solutions, this paper focuses on the criteria that

govern technology selection and how to account for them so that AOI can be effectively integrated into assembly lines. We therefore propose a generalisable framework for selecting technological solutions that guides the evaluation of key decision criteria, rather than proposing case-specific implementations.

This paper aims to answer the following questions:

- What decision-making process should companies follow when evaluating the inclusion of an AOI system in their assembly operations?
- What are the main emerging technologies that can be adopted in an AOI system?
- What key criteria should be considered when selecting the most suitable technology, given the characteristics of an assembly line?

To address these questions, the methodology first identifies a domain-agnostic set of evaluation criteria and their relative importance, as defined by a panel of experts. These weighted criteria are then used to compute multi-criteria scores, which are subsequently subjected to feasibility-exclusion checks to ensure alignment with the application-specific constraints. This design choice distinguishes this work from prior contributions that report high CV performance on tailored setups but do not formalise the upstream technology-selection problem.

The proposed methodology aims to support academics in enhancing the robustness and resilience of decision-making processes, advancing the state of the art in AOI research, and improving the transferability of academic findings to industrial applications. At the same time, it assists practitioners in making informed investment decisions and optimising the integration of AOI systems into production workflows.

The remainder of this paper is organised as follows: Sect. 2 reviews existing CV applications for AOI in assembly processes, highlighting current practices, limitations, and criteria for choosing the technological solution. Section 3 identifies key criteria for selecting image-acquisition technologies and presents the proposed methodology. Section 4 demonstrates the application of the MCDM approach through two real case studies in an automotive company. Section 5 concludes with insights into the implications of the methodology and future research directions in CV for quality assurance.

2 Literature review

This section examines the scientific literature regarding the use of CV to identify functional nonconformities resulting from assembly processes. It outlines the methodology used to

retrieve and select the scientific contributions and discusses the results with the objective of identifying the primary image-acquisition technologies, as well as the criteria for choosing among these options. The literature review adheres to the PRISMA 2020 checklist [31] to ensure the thoroughness and systematic approach of the analysed literature.

2.1 Review methodology

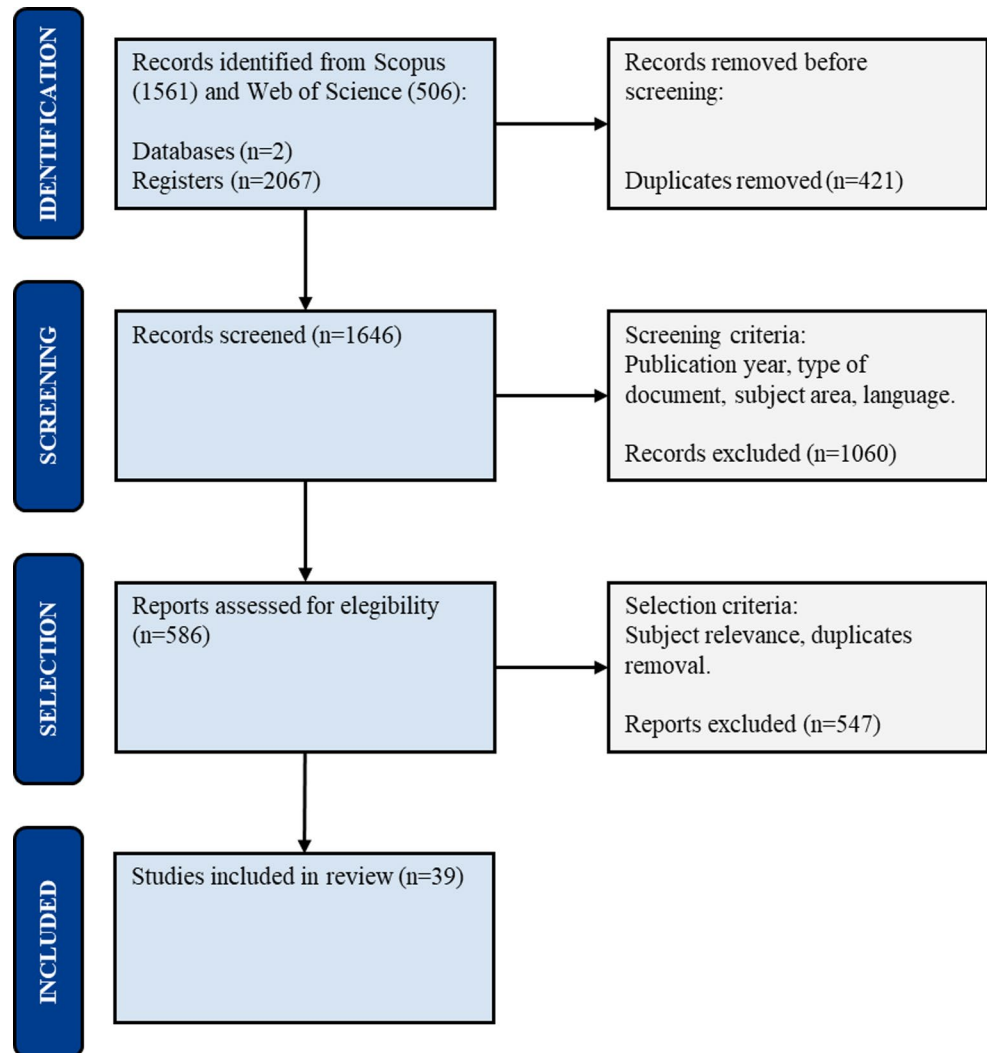
The literature review aims to systematically identify and evaluate contributions related to CV applications for detecting functional nonconformities generated in assembly processes. The methodology, designed to ensure a rigorous selection with clear and reasonable criteria, follows a multi-step process, summarised in Fig. 1.

2.1.1 Data search strategy

The literature search retrieves records from two major databases: Scopus and Web of Science. These databases are selected for their extensive coverage of high-impact journals and conference proceedings. The search queries are formulated to cover terms relating to AOI, CV and defect detection in assembly processes. The queries employed are as follows:

- **Scopus:** *TITLE-ABS-KEY (((("automatic" OR "automated") AND ("quality control" OR "optical inspection" OR "visual inspection")) OR ("computer vision" OR "machine vision") AND ("product quality" OR "inspection")) AND "assembly")*.

Fig. 1 Literature review methodology for identifying and selecting relevant contributions on AOI systems in assembly processes



- **Web of Science:** $TS=((\textit{“automatic” OR “automated”}) AND (\textit{“quality control” OR “optical inspection” OR “visual inspection”}) AND \textit{“assembly”}) OR TS=((\textit{“computer vision” OR “machine vision”}) AND (\textit{“product quality” OR “inspection”}) AND \textit{“assembly”})$.

A total of 2,067 records are obtained from these databases. Upon retrieval, removing duplicate records results in a refined dataset of 1,646 unique studies. Duplicate identification is based on metadata (title, authors, DOI).

2.1.2 Screening

The 1646 unique studies are screened according to the following inclusion criteria:

- Publication year: 2012 onwards, to reflect advancements following the introduction of AlexNet [20] and the improved performance of CNNs.
- Document type: Articles, conference papers, book chapters, reviews, and short surveys.
- Subject area: Engineering, Computer Science.
- Language: English.

This screening process results in the exclusion of 1,060 studies, leaving 586 for further assessment.

2.1.3 Selection

The 586 studies are subsequently assessed in detail for eligibility based on their pertinence to the research objectives, applying the following selection criteria:

- Subject relevance: the study must address the application of CV to detect one or more defects arising from assembly processes.
- Type of defects: only case studies addressing functional defects are included; studies on surface defects are excluded, as these are typically associated with component manufacturing rather than the assembly stage.
- Image-acquisition technology: the paper must clearly describe the technologies utilised for image acquisition.

Additionally, duplicate case studies are removed; for instance, when a conference paper and its extended journal version overlap, only the journal article is retained. After applying these criteria, 547 studies are excluded, resulting in a final set of 39 studies included in the review.

2.2 Review results

The 39 scientific papers included in the literature review are summarised in Table 1. The following classification criteria are applied to organise the data:

1. *Industrial sector*: the sector to which the case study discussed in the paper pertains.
2. *Product*: the complete product that is visually inspected, rather than just the area checked (e.g., in a vehicle assembly line where the AOI deals with brakes, the product is categorised as “car”).
3. *Inspection environment*: the location where the inspection process is conducted, distinguishing between:
 - a *Laboratory*: inspections are performed in controlled testing environments.
 - b *End of line*: inspections are conducted after the assembly process in isolated areas at the conclusion of the assembly line. Cases in which AOI is carried out off-line, with the product subsequently routed to a downstream section, also fall into this category.
 - c *In the line*: inspections are integrated within the production line during assembly or while the product moves to the next station.
4. *Adopted Technology*: the technology used for image acquisition is categorised as follows:
 - a *Camera*: traditional or advanced camera systems for capturing visual data, either fixed or, at most, semi-fixed; the camera may travel along a rail.
 - b *Robot*: systems that incorporate robotic manipulators with image acquisition tools. This category includes industrial robots, collaborative robots (cobots), and automated guided vehicles (AGVs) equipped with robotic arms.
 - c *Mobile Device*: portable devices for image capture, positioned as necessary by human operators, e.g., smartphones, tablets.
5. *Inspection Type*: each study is analysed to identify the type of quality control performed. This criterion is categorised into three main types:
 - a *Component presence/absence*: inspection to confirm whether specific components are present or absent.
 - b *Component position*: inspection focusing on verifying the correct placement of components.
 - c *Component configuration*: inspection that assesses whether assembled components are configured as intended, e.g., colour and size are correct.

Table 1 Summary of the selected case studies categorised by problem type, industrial sector, inspected product, and details of inspection methods and environments

Reference	Industrial sector	Product	Environment	Adopted technology	Inspection type		
					Component position	Component presence/absence	Component configuration
Zhou et al. [32]	Aerospace	Aviation equipment	End of line	Robot	X		
Guo et al. [33]	Electrical devices	Low-voltage apparatus	End of line	Camera	X	X	
Lin et al. [34]	Machinery and industrial equipment	Ratchet wrench	Laboratory	Camera	X	X	
Li et al. [35]	Electronics	Printed Circuit Board	End of line	Camera		X	
Zhao et al. [36]	Machinery and industrial equipment	Assembly platform	Laboratory	Mobile device	X	X	
Silva et al. [37]	Machinery and industrial equipment	Pneumatic cylinder	Laboratory	Mobile device	X	X	
Raoofi et al. [38]	Construction	Steel joist	End of line	Camera		X	
Morsi et al. [39]	Aerospace	Wing slat actuator	Laboratory	Robot	X		
Aras et al. [40]	Electronics	Printed Circuit Board	Laboratory	Camera		X	
Meng et al. [41]	Automotive	Cross-car beam	Laboratory	Camera		X	
Yousif et al. [42]	Aerospace	Rocket prototype	Laboratory	Camera		X	X
Zhu et al. [43]	Automotive	Pedal car	End of line	Camera		X	X
Shaloo et al. [44]	Machinery and industrial equipment	Piston	In the line	Camera		X	X
Huang et al. [45]	Medical	Infusion bag	Laboratory	Camera	X	X	
Zhang [46]	Electronics	Printed Circuit Board	End of line	Camera		X	X
Mumbelli et al. [47]	Automotive	Car underside	End of line	Robot	X	X	X
Staněk et al. [48]	Automotive	Car	End of line	Camera			X
Rio-Torto et al. [49]	Automotive	Car	End of line	Camera			X
Auledas-Noguera et al. [50]	Aerospace	Wing	Laboratory	Robot	X		
Frustaci et al. [51]	Automotive	Catalytic converter	End of line	Camera	X		
Maack et al. [52]	Electrical devices	Electrical article	In the line	Camera		X	
Basamaklis et al. [53]	Electronics	Monitor cover	Laboratory	Robot	X	X	
Luo et al. [54]	Automotive	Dashboard	Laboratory	Camera	X		
Saif et al. [55]	Electronics	Printed Circuit Board	Laboratory	Camera	X		
Caliskan & Gurkan [56]	Electronics	Printed Circuit Board	Laboratory	Camera		X	
Capela et al. [57]	Automotive	Car	End of line	Mobile device		X	
Zhang et al. [58]	Electrical devices	Battery	End of line	Camera	X		
Židek et al. [59]	Additive Manufacturing	Extruder filament guide	End of line	Camera		X	
Mazzetto et al. [60]	Automotive	Brake disc and calliper	In the line	Camera		X	
Rejc [61]	Machinery and industrial equipment	Thermostat	End of line	Camera	X	X	
Ben Abdallah et al. [62]	Aerospace	Aircraft Engine	End of line	Robot/Mobile Device	X	X	
Ivanovska et al. [63]	Automotive	Lamp	In the line	Robot		X	
Chauhan & Surgenor [64]	Machinery and industrial equipment	O-ring	In the line	Camera		X	
Sun & Sun [65]	Automotive	Cross-car beam	In the line	Camera	X	X	
Maiolino et al. [66]	Aerospace	Generic component	Laboratory	Robot	X		
Wen et al. [67]	Automotive	Excavator component	In the line	Camera	X	X	
Müller et al. [68]	Automotive	Car	End of line	Robot		X	
Yu & Wang [69]	Toys	Lego Wheels	Laboratory	Camera	X		
Davrajh et al. [70]	Electrical devices	Torch	End of line	Camera		X	X

2.3 Review discussion

The analysis of the 39 selected contributions provides a structured overview of how AOI systems are applied to detect functional nonconformities in assembly processes.

The automotive sector accounts for 33.3% of the reviewed studies, reflecting its stringent quality requirements and the growing complexity of its assembly processes. The electronics sector follows, representing 15.4% of the studies, with a notable focus on the application of CV in the production of Printed Circuit Boards (PCBs). Both the aerospace industry and the machinery and industrial equipment sector also represent 15.4% of the studies, highlighting their emphasis on precision and reliability in assembly. The remaining 20.5% of studies are spread across various sectors, including electrical devices, medical technology, additive manufacturing, and construction. This distribution suggests that industries adopting CV for functional inspections are primarily driven by their demand for accuracy and automation.

Additionally, high production volumes often push companies towards AOI systems, as the rapid pace of operations can make inspections challenging for human operators, who are increasingly prone to fatigue.

Regarding the types of inspections, the analysis of scientific papers reveals that AOI systems are predominantly used to verify the presence of components, appearing in 28 out of 39 cases. This result is likely due to the critical nature of this check, as missing components can lead to significant issues with product functionality and require costly rework. Component positioning inspections are less common but still relevant, occurring in 20 out of 39 cases. This type of inspection is more challenging for CV, as it requires high precision and accuracy. Configuration checks, on the other hand, are the least represented, appearing in only 8 cases. This may be because nonconformities in configuration can negatively affect customer satisfaction and brand reputation, but they do not always impact product functionality. Moreover, configuration defects are less probable in sectors where assembly lines do not accommodate multiple product variants, which limits the interest in these inspections for some sectors.

Most of the AOI systems identified in this literature review are applied in areas separate from those where component assembly occurs. In contrast, only seven cases implement automated inspection solutions directly on the assembly line. These systems face more significant constraints in terms of time and space, but offer the advantage of immediate defect detection. Additionally, 15 of the reviewed cases are prototype applications tested exclusively in laboratory settings, highlighting that CV is still in the early stages of industrial adoption. However, some scientific contributions attempt to replicate the space and time constraints typical of real-world applications [34, 37, 42, 45, 50, 54, 66].

Although all the case studies collected from the literature clearly describe the technology used for image acquisition in AOI systems, only a few contributions provide a rationale for selecting a specific technological solution. Zhao et al. [36] propose the use of a tablet to verify the presence and positioning of various components on a generic assembly platform. They compare a robotic system and a tablet, ultimately identifying the latter as the superior solution due to its enhanced safety in human interaction, greater flexibility in adapting to obstructions covering the regions of interest, lower cost, and the absence of path reprogramming requirements whenever the product design changes. Similarly, Ben Abdallah et al. [62] investigate two approaches for detailed presence and position control of aircraft engine components: one based on an AGV with a robotic arm and the other on a handheld tablet. Their study finds both technologies effective, although the tablet achieves superior defect recognition performance. These results reflect the more controlled laboratory setting used for the tablet, whereas the robot-based system was trained and tested in a real industrial environment with more challenging acquisition conditions.

The most widely adopted technology is the camera, used in 27 out of 39 application cases. One of the main reasons for its prevalence is that it represents a well-established standard solution. Analysing the application cases where cameras have been employed, this technology appears particularly suitable for inspecting small products. For instance, it is extensively used in PCB inspections [35, 40, 46, 55, 56], where a single camera is often mounted on a guide to capture multiple detailed images of the product. Additional examples of small products with clearly visible areas inspected using cameras include a ratchet wrench [34], a piston [44], an electrical component [52], a car dashboard [54], a thermostat [61], an O-ring [64], toy wheels [69], and a torch [70]. However, cameras have also been integrated into AOI systems for large products requiring multiple inspections. For example, Staněk et al. [48] and Rio-Torto et al. [49] study two systems for inspecting exterior car components, leveraging multiple strategically positioned cameras. Two similar case studies include Zhu et al. [43], which involves multiple cameras monitoring the wheels of a pedal car, and Wen et al. [67], which utilises fixed-position cameras to inspect the pipes of an excavator. An alternative approach for inspecting large products without deploying multiple stationary cameras is to move a camera along a guide, as demonstrated by Raoofi et al. [38], who describe a system designed to verify welds on a long steel joist. Cameras have proven to be effective when operating directly within assembly stations, whether in areas where human operators are working or in fully automated environments. Several studies demonstrate their integration in different settings. For instance, Shaloo et al. [44], Chauhan & Surgenor

[64], and Sun & Sun [65] describe cases where one or more cameras are installed inside automated assembly cells. In contrast, Maack et al. [52] and Wen et al. [67] propose positioning cameras above workstations where human operators perform assembly tasks. Additionally, Mazzetto et al. [60] suggest placing cameras between stations, allowing the AOI system to monitor brake discs and callipers assembled by human operators. In this setup, images are captured as the products move to the next station.

Moving on to the robot category, this includes more flexible solutions than fixed cameras. The literature presents AOI systems based on both traditional industrial robots [39, 47, 53, 63, 66, 68] and AGVs equipped with robotic arms [32, 50, 62]. Robots also demonstrate the capability to perform detailed inspections in hard-to-reach areas of large products, such as aircraft wings and engines [32, 39, 50, 62]. In the context of Industry 5.0, solutions that integrate robotic activities with human operators' tasks are particularly promising. For instance, Auledas-Noguera et al. [50] propose a system in which an AGV follows an operator during assembly tasks and provides real-time alerts if a step is executed incorrectly. Müller et al. [68] introduce an approach in the automotive sector that distributes inspection tasks between the AOI system and human operators: the robot is responsible for detecting complex defects inside the vehicle, such as identifying leaks after a water-leak test, while human operators inspect the car's external components within the same area.

The mobile device category is the least represented in the literature, with only three application cases. These solutions offer the highest flexibility in image acquisition; however, this very flexibility means that images are not captured from a standardised position, potentially making it more challenging for AI to identify nonconformities correctly. Zhao et al. [36] and Capela et al. [57] propose using handheld devices operated by human workers to capture images from appropriate positions. In contrast, Silva et al. [37] suggest using smart glasses worn directly by the operator assembling pneumatic cylinders, enabling real-time feedback during the assembly process.

The product size and the proportion of the region of interest relative to the overall product size are among the most influential factors in determining the appropriate technology. Figure 2 provides an approximate distribution of case studies based on these two parameters. The x-axis represents the product volume, expressed in m^3 , while the y-axis shows the ratio between the area to be inspected and the surface area of the corresponding side of the product. Since this ratio compares two areas, it is a dimensionless coefficient ranging from 0 to 1. From Fig. 2, it is evident that cameras are the predominant solution in the upper-left quadrant, where smaller products are represented. Cameras

are also applicable to larger products, provided that detailed inspections are not required. However, as product volume increases while the region to be inspected remains relatively small, more flexible solutions, such as robots and mobile devices, become necessary. In the lower-right quadrant, the regions of interest are small, spatially dispersed, and often partially occluded across large components. Meeting the required spatial resolution for defect detection generally entails short working distances and viewpoint adaptation. A fixed solution requires a wide-field setup, which might not provide the required level of detail or fixtures that encumber the production workflow. By contrast, robots or mobile devices can position the sensor close to each region of interest, regulate the incidence of lighting, select non-occluded viewpoints, and then vacate the area, thereby reducing occlusions and minimising interference from infrastructure and fixtures with production processes.

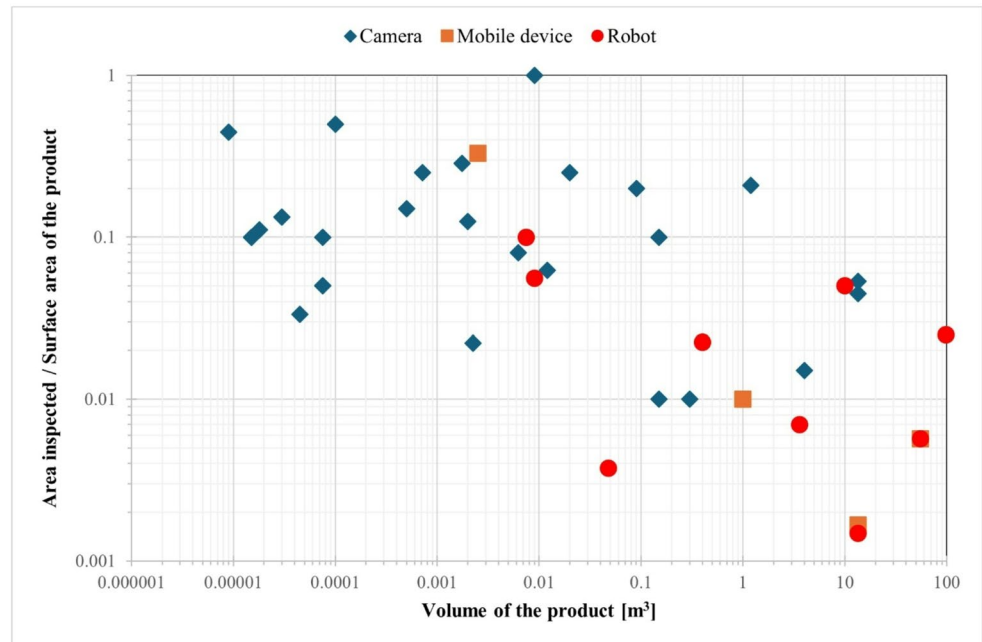
The literature highlights the growing importance of AOI in industrial quality control, emphasising its potential to enhance defect detection and reduce reliance on manual inspections. However, the reviewed studies primarily focus on the defect detection performance of CV rather than providing a comprehensive methodology for selecting the most suitable imaging technology. This paper explicitly fills that gap by systematising the key criteria that drive technology selection, thus facilitating AOI integration in real assembly environments.

Additionally, from the analysis of the literature, it emerges that key factors influencing the choice of image-acquisition technology include product dimensions and the size of the inspection area. Some studies also mention the visibility of the area to be inspected and the required system flexibility as relevant decision criteria. Furthermore, in AOI systems applied to real-world assembly lines, the primary constraints considered have been the available inspection time and spatial limitations within the production environment.

3 Methodology for selecting image-acquisition technologies in AOI systems

A careful evaluation of the image-acquisition technology is a critical step in integrating an AOI system into the assembly line. This section introduces a novel methodology to support researchers and practitioners in identifying and selecting the most appropriate solution for their specific application context, with an emphasis on simplicity, transparency, and ease of adoption in industrial settings. The proposed methodology is grounded in the Weighted Sum Model (WSM), a well-established MCDM technique [71]. Within a WSM, each alternative is assessed by assigning scores to criteria and applying the corresponding weights;

Fig. 2 Distribution of literature case studies by product volume and inspected area ratio



its overall performance is then obtained by summing these weighted scores [72]. For the development of the technology selection methodology, fifteen experts, including academics, industry practitioners, and technology providers, were involved. Their opinions were used both to define the weights of each criterion and to assess the relative performance of different technological alternatives. In particular, the weights were determined using the Analytic Hierarchy Process (AHP) [73]; the integration of AHP with WSM has demonstrated high reliability in the field of decision analysis [74]. To score the alternatives across different scenarios, the Point Allocation Method was employed [75]. This approach was chosen for its ease of use and its effectiveness in prompting experts to consider trade-offs among competing technologies explicitly.

The proposed methodology targets AOI deployments on assembly lines, where the predominant image-detectable defects are predominantly functional, such as component presence/absence, correct placement and orientation, proper connector engagement, gasket placement and continuity, and verification of mandatory labels.

3.1 Structured decision process for AOI implementation

The adoption of an AOI system in an industrial assembly line requires a structured decision-making process to ensure its technical feasibility and economic viability. Figure 3 presents a novel conceptual framework outlining the key stages of this process, organised into four main stages: the Input stage, the Selection stage, the Evaluation stage, and the Operational stage.

The decision-making process begins with the collection and analysis of all data required to design and evaluate the optimal solution for the specific application. The required data are grouped into four categories:

- Defect data: historical records of defects, including frequency, criticality, cost of rework, detection rate, and potential causes.
- Product data: product volume, number of areas to be inspected, spatial dispersion of these areas, and visibility.
- Process data: available inspection time and space for implementing the AOI system, possible interactions with human operators, and the level of automation in the area.
- Assembly system data: the flexibility required for modifications in the line layout and product design.

The first group of data is mainly used to assess economic feasibility, while the remaining three sets are employed to identify the most suitable technological solution for the given application.

Next, the Selection stage identifies the most appropriate technology for image acquisition in the given application. The selection process is based not only on technical compatibility but also on practical constraints such as system maintainability and ease of integration with existing IT infrastructure. A comparative analysis of the existing image-acquisition technologies should be performed, yielding a ranking based on predefined criteria. The choice of the technological solution is followed by the definition of all equipment and components necessary to realise the AOI system. The Selection stage concludes with a provisional

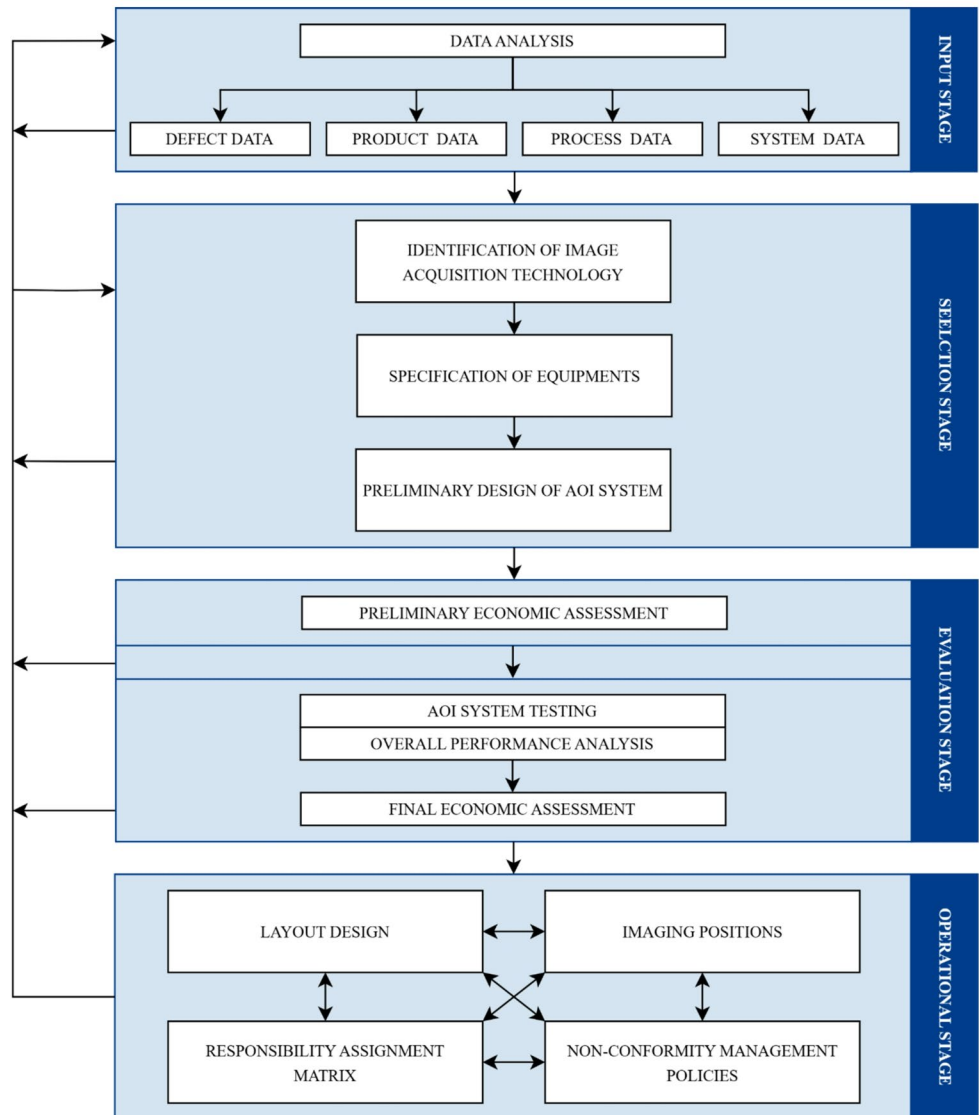
design of the system and its operation in the designated inspection area.

The Evaluation stage begins with a preliminary assessment of economic viability. If the savings from automating inspections and promptly detecting defects are insufficient to recoup the project investment within a reasonable time-frame, typically two to four years, the process returns to the previous stage to consider an alternative solution. If the project appears preliminarily feasible, a prototype version of the AOI system is deployed and tested in an environment designed to replicate real-world constraints as closely as possible. The prototype system undergoes a structured testing campaign under conditions that closely simulate the spatial and temporal constraints of the actual production line. This testing setup also replicates typical lighting conditions and accounts for potential obstacles that could interfere with image acquisition, such as machine structures, moving

parts, or operator activity in the vicinity of the inspection area. During this testing phase, specific performance metrics, such as detection accuracy, false positive and false negative rates, and image-acquisition time, are monitored to assess the system’s robustness. Where applicable, virtual prototyping environments or digital twins can also support this phase to simulate spatial and operational constraints. Subsequently, a final economic assessment of the AOI system is conducted based on the empirical performance data.

If the prototype evaluation confirms the feasibility, the process advances to the Operational stage, where final decisions are made regarding the physical implementation of the system. This stage specifies the precise location of the system components in the work area and the optimal positions for capturing images. Additionally, responsibilities related to the system are assigned, such as determining who will update the image dataset if the product changes.

Fig. 3 Structured decision-making process for AOI system implementation



The process for handling nonconformities identified by the system is also established, such as whether a reworked product should undergo the AOI again. A maintenance and calibration schedule is also defined at this stage to ensure the system maintains high accuracy over time. Establishing clear protocols for troubleshooting and system updates is crucial to minimising downtime and ensuring continuous improvement.

It is important to note that the framework is designed to be iterative: if any stage reveals technical or economic infeasibility, the process loops back to revising earlier decisions, ensuring flexibility and continuous improvement. Moreover, feedback from each stage should be communicated to management, as this may lead to valuable insights for future projects.

The present study focuses specifically on the Selection stage of the framework, which is rarely addressed in the literature despite being a critical step for the effective integration of AOI systems in real-world industrial settings.

3.2 Technological alternatives for image acquisition

The core of the Selection stage involves identifying the optimal image-acquisition technology to provide reliable visual input to CNNs. As discussed in Sect. 2, the state of the art in both commercial and experimental technologies comprises three primary alternatives: fixed cameras, mobile devices, and robots. The choice of the most suitable solution strongly depends on the specific application requirements and production environment, thus making a well-informed decision essential. To support the comparison, the technologies are evaluated based on the following criteria, as summarised in Table 2:

- *Accuracy and Consistency*: the system’s ability to acquire images reliably, considering repeatability, sensor stability, and environmental control. These aspects are all critical for effective defect detection.
- *Scalability*: how effectively the system can be expanded or adapted to incorporate additional inspection tasks, whether they are similar to those it already performs or completely different.

Table 2 Overview of the characteristics of image-acquisition technologies

	Mobile device	Camera	Robot
Accuracy and Consistency	↑	↑↑↑	↑↑
Scalability	↑↑↑	↑	↑↑
Adaptability	↑↑↑	↑	↑↑
Ease of integration	↑↑↑	↑↑	↑
Image-acquisition time	↑↑↑	↑	↑↑↑
Capital Expenditure (CAPEX)	↑	↑↑	↑↑↑
Operational Expenditure (OPEX)	↑↑↑	↑	↑

- *Adaptability*: the ability of the solution to cope with changes in product design, layout, or operating conditions with minimal reconfiguration and downtime.
- *Ease of integration*: how readily the solution can be embedded into the existing production process. It encompasses compatibility with current machinery and workflows, simplicity of installation, and minimal impact on production speed.
- *Image-acquisition time*: the time required to capture the necessary images.
- *Capital Expenditure (CAPEX)*: the initial investment required for acquisition and installation.
- *Operational Expenditure (OPEX)*: the recurring annual costs for maintenance, energy consumption, and human supervision.

Mobile devices offer the easiest solution for incorporating into assembly lines, as they do not require dedicated space and necessitate minimal investment. Their flexible positioning allows for easy adaptation to changes in the work area or product. However, their use typically relies on human operators to position devices correctly, resulting in increased OPEX and longer image-acquisition times. Moreover, the lack of standardisation in image acquisition may reduce overall system performance and model generalisation.

Fixed or semi-fixed cameras offer high accuracy and consistency due to their stable, standardised positioning. They operate autonomously and are suitable for high-throughput environments. Nevertheless, their lack of flexibility may become a limitation in settings where frequent process changes occur. They require a moderate initial investment and have relatively low running costs.

Robots provide flexible and repeatable image acquisition, especially in complex or hard-to-reach inspection areas. However, they involve higher capital costs and may be more challenging to integrate into crowded workspaces, particularly when human–robot collaboration is required. In addition, acquisition times are generally longer and must be reduced through path-planning optimisation.

In general, mobile devices are best suited for flexible, low-volume applications, while fixed cameras represent the best choice for standardised and high-throughput contexts. Robotic systems, although requiring a higher initial investment and longer acquisition times, offer a promising compromise in environments that demand both adaptability and precision.

Low-mix contexts entail repetitive viewpoints and benefit from fixed solutions that maximise repeatability and measurement stability; conversely, high-mix or highly customised products require model- or variant-specific viewpoints, favouring flexible solutions (robot-mounted or mobile/handheld) that can be repositioned as needed.

3.3 Definition and prioritisation of decision criteria

To support the structured selection of the most suitable image-acquisition technology, a set of decision criteria was defined through a series of interviews with fifteen experts from academia and industry. At the outset, participants were informed that the objective was to derive a domain-agnostic set of criteria that would enable neutral technology screening. The resulting criteria were intended to be transferable across case studies with markedly different characteristics, while still capturing the key product- and process-level attributes that most strongly discriminate among image-acquisition technologies. Based on their feedback, four main criteria were identified as most relevant for evaluating the appropriateness of a given technology for a specific application. In the proposed methodology, each criterion can be assigned a level of Low (L), Medium (M), or High (H).

The first criterion, *Product Dimensions*, is evaluated by considering the combination of Product Volume (PV) and Inspected Area Ratio (IAR). These two parameters are defined as follows:

1. *Product Volume* (PV), expressed in m³:
 - L: less than 0.001 m³.
 - M: between 0.001 and 1 m³.
 - H: more than 1 m³.
2. *Inspected Area Ratio* (IAR), a dimensionless coefficient ranging from 0 to 1, represents the ratio between the area to be inspected and the surface area of the corresponding side of the product (as introduced in Sect. 2):
 - L: less than 0.01.
 - M: between 0.01 and 0.1
 - H: more than 0.1.

PV and IAR are jointly assessed because their combined effect provides a more comprehensive representation of the spatial characteristics of the inspection task, playing a critical role in differentiating among technological alternatives, as previously discussed in Sect. 2. Based on the three-level classification of each parameter, this criterion defines a total of nine possible scenarios.

The other three criteria are considered individually, each with three possible levels, and are defined as follows:

3. *Dispersion of inspected areas*, referring to the number and spatial distribution of the areas to be inspected. A higher dispersion level implies greater image-acquisition

complexity, as more images are required and the system must offer greater adaptability:

- L: 1–2 images required.
 - M: from 3 to 10 images required.
 - H: more than 10 images required.
4. *Visibility of inspected areas*, assessing how easily the regions of interest can be accessed or visualised during image acquisition:
 - L: some areas are difficult to access or only partially visible, requiring specific angles or close-up views.
 - M: certain regions are clearly visible only at close range.
 - H: all areas are clearly visible even from a distance.
 5. *Flexibility requirements*, indicating how frequently the AOI system must adapt to changes in layout or product design:
 - L: changes to industrial layout or product design every 3 months.
 - M: changes to industrial layout or product design every year.
 - H: rare changes to industrial layout or product design.

To determine the relative importance of each criterion, AHP was applied. Experts were asked to make pairwise comparisons between criteria, expressing their judgements using the Saaty scale [73], which ranges from 1 to 9. A value of 1 indicates that the two criteria are equally important, whereas 9 indicates that one criterion is extremely more important than the other. To aggregate their individual judgements, the geometric mean was applied to each corresponding element of the pairwise comparison matrices. This method is commonly used in AHP because it preserves the reciprocal property of the matrix, ensuring that if criterion A is rated n times more important than criterion B, then B is rated $1/n$ as important as A [76].

Table 3 presents the aggregated pairwise-comparison values between criteria. It also shows the final weights assigned to each criterion, calculated using the eigenvector method.

The consistency of the judgement matrix was evaluated by computing the Consistency Ratio (CR). In this case, the CR is 0.0295, which is well below the commonly accepted threshold of 0.10, indicating a high level of consistency in the expert responses.

3.4 Weighted scoring of technological alternatives

Once the criterion weights are determined, the model evaluates each technological alternative by assigning scenario-specific scores for every criterion. To this end, the Point Allocation Method was applied: in this phase, each expert allocated five points among the three alternatives for each scenario. This approach was selected for its simplicity and effectiveness in encouraging experts to make explicit trade-offs. By limiting the total points available, the method pushed participants to consider whether one technology clearly outperforms the others or whether their performance is comparable.

The scores assigned to each technology in each scenario were calculated by averaging the fifteen experts’ scores. The resulting aggregate scores are shown in Fig. 4, which also illustrates the complete application of the WSM. Once the applicable scenario is identified for each criterion, four partial scores are retrieved from the tables in Fig. 4 for each candidate technology T :

- The Dimensional score D_T is based on the combination of PV and IAR.
- The Scattering score S_T is derived from the dispersion of inspected areas.
- The Visibility score V_T is based on the accessibility of the inspected regions.
- The Flexibility score F_T is related to the adaptability required by the system.

The model then calculates a final score FS_T for each technology T as the weighted sum of these four partial scores, using the weights defined in Sect. 3.3, as detailed in Eq. (1):

$$FS_T = 0.419 \bullet D_T + 0.098 \bullet S_T + 0.289 \bullet V_T + 0.193 \bullet F_T \quad (1)$$

The technology with the highest FS_T value is considered the most suitable solution for the analysed application. However, before confirming the selection, the model applies a set of exclusion criteria to ensure that the proposed solution is viable from an operational standpoint. The following conditions must be satisfied:

1. Image-acquisition time: the technology must allow image capture within the available inspection time window.
2. Space constraints: the system must physically fit within the designated area of the assembly line.
3. Interaction with human operators: if the inspection area is shared with operators, the solution must ensure safe and effective interaction.
4. Automation compatibility: if the area is fully automated, the technology must be suitable for integration into the existing system.

If the top-ranked technology does not satisfy one or more of these constraints, it is excluded, and the next highest-ranked acceptable option is selected. These exclusion conditions are applied after WSM scoring and before final selection, acting as hard feasibility filters. This mechanism preserves methodological generality while remaining sensitive to the distinctive constraints of each case study.

4 Case studies

In this section, the proposed methodology for selecting an image-acquisition technology in an AOI system is applied to two real-world case studies from a leading Italian manufacturer of high-performance supercars. For a company that produces premium vehicles, ensuring product conformity before delivery is essential. At the same time, quality control systems must integrate seamlessly into existing production processes.

4.1 AOI of vehicle exterior components

The first case study focuses on verifying that the configuration of exterior components matches the customer’s order. This includes checking the colour and shape of more than 20 external car body parts, which are distributed across the vehicle, e.g., bumpers, rims, license plate holders, and spoilers.

The designated area for implementing the AOI system is an inspection station at the end of the assembly line. This area is a confined space, situated within a tunnel that offers stable and consistent lighting via LED illuminators. Human operators are also expected to continue working in this space, conducting additional inspections. The cars enter the area via a conveyor system, which ensures standard positioning.

Regarding the selection of the optimal image-acquisition technology, partial scores were assigned based on the following considerations:

Table 3 Aggregated pairwise comparison matrix and resulting weights for decision criteria

	Dimensions	Dispersion	Visibility	Flexibility	Weight
Dimensions	1	3.634	1.838	2.111	0.419
Dispersion	0.275	1	0.382	0.382	0.098
Visibility	0.544	2.621	1	2.169	0.289
Flexibility	0.474	2.621	0.461	1	0.193

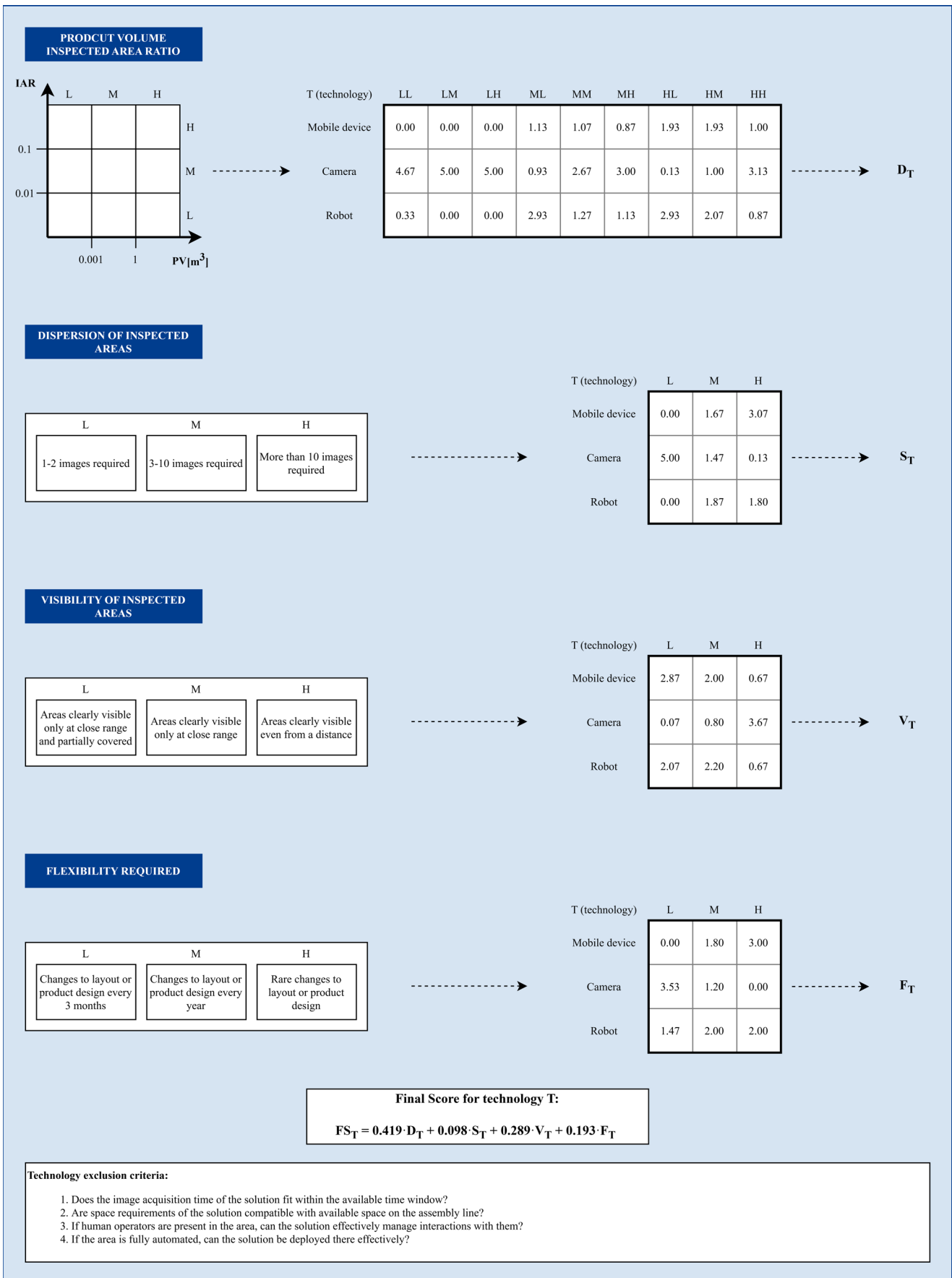


Fig. 4 MCDM approach for identifying the most suitable image-acquisition technology

- **Product Dimensions:** The vehicle has a volume greater than 1 m³ (high PV), while the IAR of the components falls between 0.01 and 0.1 (medium IAR), resulting in an HM scenario.
- **Dispersion:** The components are distributed across the car body but can be effectively captured in eight images (three per side, one front, one rear), resulting in a medium level of dispersion.
- **Visibility:** All components are clearly visible even from a distance, resulting in a high visibility score.
- **Flexibility:** Although the station layout rarely changes, the vehicle model is typically updated annually. Therefore, the flexibility requirement is medium.

Based on these inputs, the final scores for the candidate technologies, computed using the WSM, are:

1. Camera: 1.86.
2. Robot: 1.63.
3. Mobile device: 1.51.

Among the three alternatives, the camera-based solution achieves the highest final score, making it the most suitable option according to the model. The solution also satisfies all the operational constraints: it allows image acquisition within the available inspection time window, fits within the confined space of the tunnel, and ensures safe coexistence with human operators already working in the area. A fixed-camera setup, consisting of eight strategically positioned units, emerges as the most effective solution: it ensures full component coverage with minimal disruption to the inspection workflow and seamless integration into the existing production environment.

Although this analysis follows the formal steps of the method, it is also helpful to consider a counterexample of a technology that, while potentially effective in terms of scoring, would not meet the operational constraints. Robotic systems could, in principle, be considered for this task; however, their deployment in confined environments typically poses challenges related to space constraints, human–machine interaction, and operational safety. These factors would likely prevent them from meeting the exclusion criteria in this specific context.

Figure 5 summarises the application of the methodology to this case study, illustrating the scenario classification, scoring, and final technology selection.

4.2 AOI of chassis and engine

The second case study focuses on verifying the presence and correct positioning of components located in the lower part of the vehicle, including elements of the chassis and engine. This inspection is particularly critical, as the lower body is subsequently joined to the upper body during the so-called “marriage” process, making rework operations both complex and costly. The AOI system is intended to be deployed in a buffer station where the platform remains stationary for approximately seven minutes before being transported by an automated guided vehicle (AGV) to the *marriage* station.

The evaluation of the four decision criteria for this application leads to the following scenario classification:

- **Product Dimensions:** The assembly volume exceeds 1 m³ (high PV), but the inspected components are relatively small, resulting in an IAR of less than 0.01. This corresponds to an HL scenario.
- **Dispersion:** Due to the large number and small size of the components, dozens of images are required to ensure complete coverage, resulting in a high dispersion level.
- **Visibility:** Some components are partially obscured by structural elements of the platform, making visual access challenging. Visibility is therefore classified as low.
- **Flexibility:** As in the previous case, annual updates to product configurations or work area layout are possible, resulting in a medium level of flexibility.

Based on these inputs, the final scores calculated using the WSM are:

1. Robot: 2.39.
2. Mobile device: 2.29.
3. Camera: 0.32.

The robotic solution achieves the highest score and is thus selected as the most suitable technology. The proposed system comprises an AGV equipped with a collaborative robotic arm, enabling it to navigate around the vehicle platform and capture images from multiple angles. The available seven-minute window is sufficient to complete the image acquisition, and the space in the buffer area is adequate to support robot movement. Furthermore, the area is not occupied by human operators during the inspection phase. Nevertheless, the use of a collaborative robot ensures compliance with safety requirements, even in the event of unexpected human presence in the area.

	Dimensions: HM	Dispersion: M	Visibility: H	Flexibility: M	Final Scores
Mobile device	0.419 · 1.93	0.098 · 1.67	0.289 · 0.67	0.193 · 1.80	1.51
Camera	0.419 · 1.00	0.098 · 1.47	0.289 · 3.67	0.193 · 1.20	1.86
Robot	0.419 · 2.07	0.098 · 1.87	0.289 · 0.67	0.193 · 2.00	1.63

↓

	Image acquisition time constraints	Space availability	Interaction with humans	Automation compatibility
Camera	✓	✓	✓	not needed

Fig. 5 Selection of the technology for exterior components inspection

Figure 6 summarises the application of the methodology to this case study, illustrating the scenario classification, final scores, and selected solution.

5 Conclusion and further research directions

In an increasingly competitive industrial context, manufacturing companies must ensure high quality while maintaining efficiency. AOI represents a significant technological advancement in quality control, enabling more accurate Defect Detection and reducing nonconformities. However, selecting the most suitable AOI solution remains complex, as each technology presents different trade-offs in terms of adaptability, image-acquisition time, and scalability.

This paper has introduced a novel MCDM methodology to support the selection of image-acquisition technologies for AOI systems in industrial assembly lines. The approach combines AHP and WSM to evaluate alternative technologies based on key criteria, including product dimensions, dispersion of the inspection areas, visibility constraints, and system flexibility. It focuses on functional defects, which are the most prevalent on assembly lines, and employs domain-agnostic criteria, that are generalisable to any manufacturing sector.

The methodology has been validated through two real-world case studies in the automotive sector with differing features and requirements, demonstrating its applicability and effectiveness in guiding the design of AOI to the specific context of use. The procedure is also scalable across large production lines, considering multiple AOI units, with results that can be aggregated at the line level to reduce investment costs.

Beyond case-specific results, the contribution of this paper lies in reframing the problem from ad-hoc performance optimisation to technology selection under practical implementability constraints. By doing so, the proposed methodology enhances the decision-making process for AOI implementation and facilitates the transfer of academic insights into operational tools that are usable by industrial practitioners. It also enables companies to make more informed investment decisions and optimise the integration of AOI systems within existing workflows. The proposed selection framework is therefore aligned with the ZDM paradigm, facilitating the effective implementation of technological solutions that enhance the Defect Detection process.

Despite its contributions, this paper has certain limitations that merit consideration. First, the methodology has been validated through a limited number of case studies, providing only an initial indication of its generalisability across other industrial sectors. Second, the weighting and

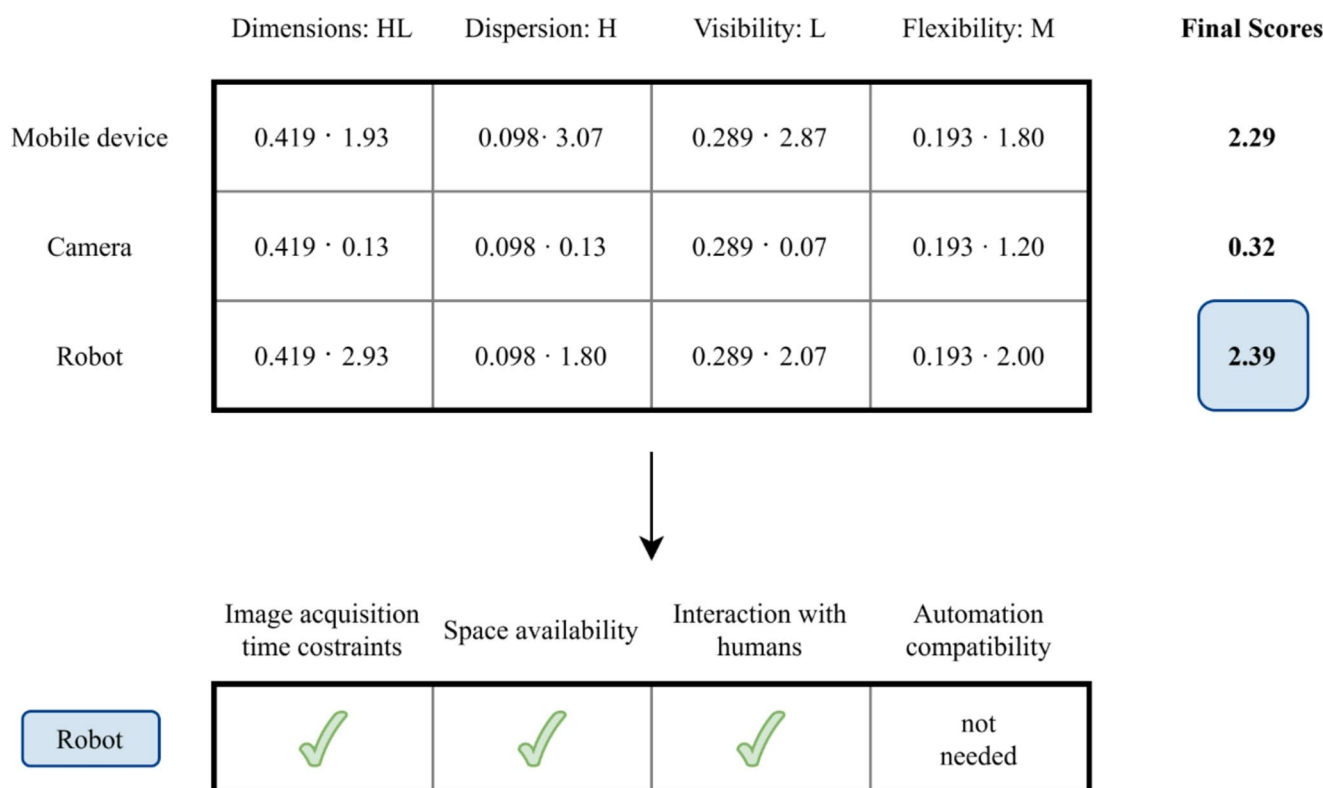


Fig. 6 Selection of the technology for chassis and engine inspection

scoring process relies on a panel of 15 experts, which may introduce biases. Finally, the proposed framework focuses on identifying the most suitable image-acquisition technology and does not yet incorporate an explicit economic evaluation of alternative options, such as payback period and long-term benefits.

Future research may address these limitations by extending the empirical validation to additional industrial contexts, involving a broader set of experts, and integrating explicit economic assessment models to support investment decisions. Furthermore, a guided user-interface tool that standardises the criterion-evaluation phase, providing built-in helpers (e.g., illustrative images, examples, and tooltips mapping inputs to qualitative scales), and generates instant AHP–WSM results with a concise decision report, could facilitate practical adoption and improve consistency. In addition, leveraging AOI data streams in combination with relevant process information to enable real-time analytics and AI-assisted feedback for Defect Prediction would support adaptive inspection strategies and more responsive quality control. Finally, designing decision-support frameworks to facilitate the adoption of emerging operator-assistance technologies, including Augmented Reality (AR) for operator guidance, standardised work, error-proofing during assembly and rework, and reducing training time and cognitive load, offers a further avenue for strengthening Defect

Prevention, in line with the approach proposed for AOI in this paper.

Author contributions Michele Ronchi (Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization).

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Mauro Gamberi (Conceptualization, Resources, Writing – review & editing, Supervision).

Cristian Cafarella (Methodology, Formal analysis, Writing – original draft, Visualization).

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