Review of Applied Science and Technology

Volume: 2; **Issue:** 4
Pages: 194 – 227

Robotics and Computer Vision for Automated Inspection of Substation and Treatment-Facility Electrical Infrastructure

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Doi: 10.63125/tfh15j12
Received: 12 September 2023; **Revised:** 20 October 2023; **Accepted:** 20 November 2023; **Published:** 25 December 2023

Abstract
This study addresses a persistent problem in safety critical electrical infrastructure inspection: robotics and computer vision pilots often show promising fault detection, but many organizations fail to operationalize these systems into compliant, auditable, and CMMS linked inspection workflows, limiting scalable adoption in substations and treatment facility electrical environments. The purpose of the study was to quantify, using real enterprise cases, how field capability and organizational enabling conditions influence perceived inspection effectiveness and adoption intention for robotics plus computer vision inspection supported by cloud and enterprise integration. A quantitative, cross sectional, case-based design was applied across two enterprise contexts, with $N = 214$ valid survey responses (substation cases $n = 112$, 52.3%; treatment facility cases $n = 102$, 47.7%) from maintenance engineers, inspection technicians, safety officers, and supervisors. Key variables included Robot Mobility and Coverage (MC), Vision Reliability and Evidence Quality (VR), Environmental Robustness (ER), Integration Readiness (IR), Safety and Procedure Compatibility (SP), Inspection Effectiveness (IE), Safety Improvement Perception (SIP), and Adoption Intention (AI); construct reliability was strong (Cronbach's alpha = 0.82 to 0.90). The analysis plan used descriptive statistics, internal consistency testing, Pearson correlation, and multiple regression models, with IE predicted by MC, VR, and ER, and AI predicted by IR, SP, and IE. Headline findings showed SIP was highest ($M = 4.22$, $SD = 0.58$) and VR was also high ($M = 4.10$, $SD = 0.63$), while IR was lowest ($M = 3.61$, $SD = 0.71$), indicating that workflow and systems integration remain the main adoption bottleneck. Correlation results indicated IE was most strongly associated with VR ($r = 0.61$, $p < .001$), and AI was strongly related to IR ($r = 0.56$, $p < .001$) and IE ($r = 0.58$, $p < .001$). Regression results showed VR was the strongest predictor of IE ($\beta = 0.39$, $p < .001$), with MC ($\beta = 0.21$, $p = .002$) and ER ($\beta = 0.18$, $p = .006$) jointly explaining $R^2 = 0.49$. Adoption intention was driven primarily by IR ($\beta = 0.31$, $p < .001$), followed by IE ($\beta = 0.28$, $p < .001$) and SP ($\beta = 0.19$, $p = .004$), explaining $R^2 = 0.54$. Case level implications indicate that organizations should treat robotics plus computer vision inspection as an enterprise pipeline rather than a device purchase: prioritize high criticality assets where weighted IE was highest (4.31 in substations; 4.12 in treatment facilities), and accelerate adoption by improving CMMS integration readiness ($M = 3.34$) and formalizing procedural permissions for routine robot routes ($M = 3.29$) alongside evidence traceability and governance.

Keywords
Robotic inspection; Computer vision; Integration readiness; Safety procedure compatibility; Adoption intention;

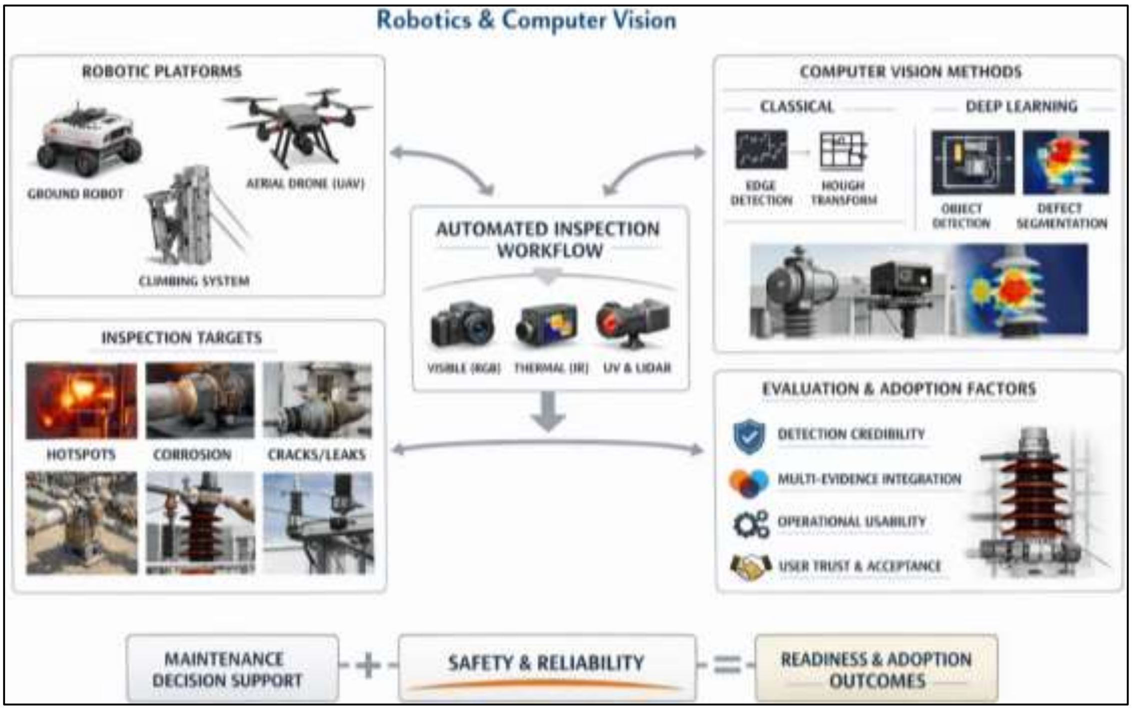
INTRODUCTION

Robotics and computer vision are commonly defined in engineering literature as complementary disciplines for building physical agents that sense, reason, and act in real environments using computational perception (Ahmad et al., 2020). Robotics, in an infrastructure context, refers to embodied electromechanical systems that execute inspection tasks through mobility, manipulation, and autonomous or semi-autonomous decision routines, often operating under constraints such as electromagnetic interference, occlusions, and safety clearances that are characteristic of energized industrial sites (Bagavathiappan et al., 2013). Computer vision, in turn, denotes algorithmic methods that extract structured information from imagery and video—such as detection, segmentation, localization, and classification—so that assets and anomalies can be identified consistently across variable backgrounds and lighting conditions. "Automated inspection" is therefore used to describe inspection workflows where sensing and interpretation are performed with minimal manual intervention, producing repeatable condition evidence for maintenance decision-making (Ceron et al., 2014). The international significance of this topic is grounded in the essential role of substations and treatment-facility electrical infrastructure in national power continuity, public health service delivery, and industrial productivity (Girshick, 2014).

Substations concentrate, transform, and switch power in ways that directly affect grid stability, and their electrical assets—busbars, insulators, breakers, disconnectors, instrument transformers, and protection components—operate in environments where localized overheating, corrosion, contamination, mechanical loosening, and insulation deterioration can accumulate into failure modes with system-wide impacts. In treatment facilities, electrical infrastructure such as switchboards, motor control centers, drives, and distribution networks is tightly coupled to pumps, aeration systems, dosing units, and supervisory control architectures; the reliability of these electrical components is strongly associated with the continuity of water and wastewater processes that are safety-critical for communities (Nguyen et al., 2018). Within this setting, robotics is treated as the "access enabler," bringing sensors to constrained or hazardous zones, and computer vision is treated as the "interpretation engine," converting visual and thermal evidence into measurable indicators of asset condition. These definitions frame automated inspection as a measurable sociotechnical system where the physical platform, sensing modalities, and analytical models collectively shape the credibility of detected faults and the trustworthiness of maintenance decisions (Mirallès et al., 2014).

Electrical infrastructure inspection has traditionally relied on scheduled patrols, handheld measurements, and expert visual judgment, often documented through checklists and condition grades (Matikainen et al., 2016). This practice has long been recognized as labor-intensive and vulnerable to inconsistent interpretation across technicians, shifts, and environmental conditions (Liu et al., 2015). Infrared thermography (IRT) is frequently described as a non-contact condition monitoring approach that visualizes surface temperature distributions and supports the identification of thermal anomalies associated with elevated resistance, imbalance, insulation issues, and degraded connections in energized equipment. A key motivation for combining robotics and vision is that inspection quality is frequently linked to how reliably data can be acquired under operating conditions and how systematically anomalies can be characterized once captured (He et al., 2016). Reviews of IRT applications emphasize that meaningful diagnosis depends on factors such as emissivity assumptions, camera angle, distance, load variation, and environmental influences, which are especially relevant for outdoor substation yards and plant environments where solar loading, wind, and humidity distort apparent temperatures (Guo et al., 2020). Computer vision methods provide a pathway to formalize this diagnostic step by learning visual signatures of "normal" versus "abnormal" components, enabling repeatable detection across large image sets without requiring that every frame be read manually. In aerial and mobile inspection contexts, the same motivation appears in the literature on power networks, where conventional helicopter and foot-patrol methods are described as expensive, slow, and risky, while automated inspection aims to reduce exposure and improve repeatability in asset assessment (Huang et al., 2017).

Figure 1: Sociotechnical Model of Robotic and Vision-Based Inspection for Electrical Infrastructure



The critical inspection targets relevant to substations and treatment-facility electrical rooms often include hotspots at terminals, anomalous heating at breaker contacts, corrosion and contamination patterns on insulators, missing hardware, surface cracks, oil leaks, and irregular component geometry (Jadin & Taib, 2012). These conditions are observable in different imaging spaces—visible RGB, infrared, ultraviolet pulse signals, and LiDAR geometry—each contributing complementary evidence for condition assessment. As a result, automated inspection systems are often conceptualized as "measurement chains," where platform stability and sensing configuration influence signal quality, and signal quality influences the statistical credibility of findings used in correlation and regression modeling. This chain is central to quantitative cross-sectional case-study designs that aim to associate perceptions of system performance (e.g., detection credibility, ease of integration, operational usefulness) with measurable acceptance and readiness outcomes (Li et al., 2021).

Robotic inspection platforms in electrical infrastructure contexts are commonly described along three mobility families: ground mobile robots, aerial robots (UAVs), and specialized systems such as climbing or rail-guided mechanisms. Ground robots are often positioned as suitable for substation yards and industrial corridors where navigation can be constrained by equipment footprints, cable trenches, fences, and restricted safety clearances, and where repeatable patrol routes and proximity sensing support systematic image capture of the same components over time (Katrašnik et al., 2010). Aerial robots are repeatedly discussed in the power network inspection literature because they provide rapid access to elevated structures and broad spatial coverage; the same physical advantages translate to treatment-facility exterior electrical structures and overhead distribution lines that connect facilities to substations. Within UAV inspection, perception and control are tightly linked: the ability to detect and track power lines or assets in real time often becomes a prerequisite for safe navigation and stable imaging, which directly affects the interpretability of captured frames (Lin et al., 2017). Climbing and hybrid mechanisms are discussed as approaches for close-up inspection of conductors and line components where proximity is needed for high-resolution imagery; in substations, analogous logic applies to close inspection of insulators, bushings, and connection points that present small, high-consequence defects (Jalil et al., 2019). Across these platform types, the literature emphasizes that automation is not only about mobility but also about the integration of onboard sensing, communications, and analytics that translate raw data into condition statements. This integration becomes particularly important in case-study environments where operational constraints vary by site:

some substations are open-air with sunlight variability, while many treatment facilities contain indoor electrical rooms with reflective surfaces, humid conditions, and cluttered cable runs (Ronneberger et al., 2015). These variations are commonly treated as “domain shift” drivers that challenge purely handcrafted vision pipelines and motivate learning-based models that adapt better to diverse backgrounds and noise conditions (Venkatesh et al., 2012). The relevance of these platform distinctions to a quantitative survey-and-modeling study lies in how platform capabilities translate into user-perceived usability, safety, completeness of inspection coverage, and confidence in defect claims. Those perceptions can be operationalized through Likert-scale constructs and linked statistically to deployment readiness and integration friction outcomes in cross-sectional data (Wang et al., 2020).
Computer vision methods used for automated inspection in electrical infrastructure are often categorized as classical feature-based pipelines and deep learning–based perception models. Classical approaches in power line contexts have included edge and line detection, Hough-transform variations, geometric constraints, and structured search methods designed to extract slender conductors and repetitive component patterns in challenging aerial scenes. These approaches are often paired with post-processing that links segments into continuous lines or isolates regions of interest for component-level analysis (Zheng et al., 2019). Deep learning approaches are typically discussed as improvements in robustness, enabling models to learn discriminative representations for object detection and segmentation under clutter, lighting variations, and complex textures. In transmission and distribution applications, convolutional features have been used to improve power line detection for UAV navigation and inspection, reflecting the importance of stable perception for collecting high-quality imagery and producing consistent inspection outputs. For substation-like components, the literature on insulator detection and recognition is especially relevant because insulators represent a frequent defect locus (contamination, cracks, missing parts, flashover risk) and also serve as visually distinctive targets for validating inspection algorithms. Methods for insulator detection and recognition appear across multiple modalities and model types, including learning-based and structured approaches that emphasize reliability under background clutter and viewpoint changes (Zhou et al., 2016). Vision-based fault detection studies also describe defect classes that are observable visually (broken or missing insulators, corroded conductors, mechanical damage) and thermally (hotspots). For example, UAV-based multi-modal approaches combine visible and infrared evidence, supporting anomaly identification as a fused interpretation rather than a single-sensor judgment. A key theme across these works is the translation of visual outputs into inspection claims: bounding boxes, masks, or classified states are then treated as evidence that must be calibrated to reduce false positives and to produce stable confidence estimates (Girshick, 2014). This is particularly relevant to trustworthiness in a thesis context because confidence is not merely a model score; it is a decision variable that affects whether maintenance teams accept an alert, schedule corrective work, or disregard a detection as noise. In quantitative research designs that assess adoption and effectiveness perceptions, these algorithmic realities become survey-measurable constructs, such as perceived detection credibility, perceived risk reduction, and perceived effort required to validate findings (He et al., 2016).
This study is designed to achieve a set of tightly aligned objectives that translate the core idea of robotics- and computer-vision–enabled automated inspection into measurable, case-grounded outcomes for substations and treatment-facility electrical infrastructure. The first objective is to identify and operationalize the most relevant technical capability factors that shape automated inspection performance in these environments, focusing on robotics mobility and coverage capability, sensing stability, computer-vision reliability, and environmental robustness as practical dimensions of inspection quality. The second objective is to quantify how operational and organizational readiness variables influence the feasibility of implementing automated inspection within real maintenance workflows, including integration readiness with maintenance management systems, compatibility with safety procedures and standard operating protocols, training readiness, and the perceived effort required for verification and documentation. The third objective is to measure perceived inspection effectiveness as an outcome construct that captures completeness of coverage, consistency of defect recognition, timeliness of reporting, and clarity of evidence for maintenance decision-making, thereby enabling a structured comparison of perceived performance between substation settings and treatment-facility electrical settings within a cross-sectional design. The fourth objective is to

statistically test the strength and direction of relationships among the study constructs using descriptive statistics to characterize respondent perceptions, correlation analysis to determine association patterns, and regression modeling to estimate the predictive influence of selected technical and readiness factors on inspection effectiveness and adoption intention. The fifth objective is to produce study-specific trustworthiness outputs by embedding results that reflect engineering reality, including asset-criticality–weighted findings that prioritize the components with the highest operational consequence, a deployment readiness and integration friction score that summarizes practical implementation barriers, and a risk–confidence mapping of automated detection claims that differentiates between defect types by consequence and perceived verification burden. The sixth objective is to synthesize the empirical findings into a structured evidence base that supports coherent hypothesis testing and clear objective fulfillment within a quantitative, cross-sectional, case-study–based framework, ensuring that each objective is assessed through explicit measurement items, transparent statistical reporting, and facility-relevant result breakdowns across the two case contexts.

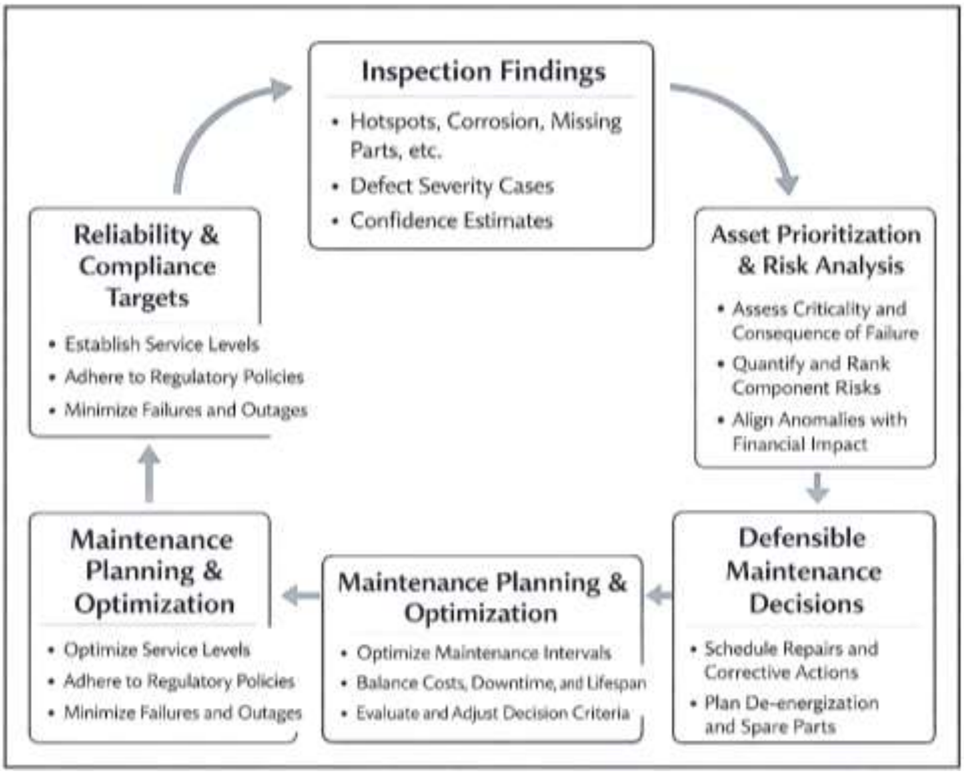
LITERATURE REVIEW

The literature on robotics and computer vision for automated inspection spans several intersecting streams that together explain how inspection tasks can be mechanized, measured, and validated in complex electrical infrastructure such as substations and treatment-facility electrical systems. At a foundational level, inspection research in power and industrial environments emphasizes the operational importance of early anomaly identification, consistent condition documentation, and safe access to energized or restricted zones, which motivates the use of robotic platforms to extend inspection reach while standardizing data acquisition under repeatable routes and viewpoints. In parallel, computer vision literature contributes methods that convert imagery into actionable condition evidence through detection, segmentation, and classification pipelines, enabling asset recognition and defect identification at scale and under diverse lighting, clutter, and weather conditions. A third stream focuses on sensing modalities and inspection evidence quality, highlighting how visible imaging, infrared thermography, ultraviolet sensing, and 3D mapping each capture different aspects of degradation and therefore influence the reliability of inspection conclusions, especially for anomalies such as overheating signatures, corrosion patterns, insulation damage indicators, mechanical loosening cues, and contamination effects. A fourth stream concentrates on end-to-end system deployment, describing how robotics and vision must be integrated with navigation, communications, safety rules, and maintenance workflows so that inspection outputs can be verified and translated into work orders, audit trails, and operational decisions. The literature also distinguishes between outdoor substation yards and plant-like indoor electrical rooms, noting that environmental variability, humidity, reflective surfaces, congestion, and access constraints create different noise sources and verification requirements that shape both engineering feasibility and user confidence in automated defect claims. Finally, applied technology adoption research offers constructs for explaining why technically capable systems succeed or stall in operational environments, emphasizing perceived usefulness, perceived effort, enabling conditions, and trust in system outputs as measurable variables that interact with organizational readiness. Taken together, these streams provide the intellectual basis for building a study-specific model that links robotic mobility and sensing capability, computer vision reliability, integration readiness, and risk perception to perceived inspection effectiveness and implementation readiness in substations and treatment facilities, while also supporting quantitative testing through structured constructs that can be measured via Likert-scale instruments and analyzed using descriptive statistics, correlation patterns, and regression relationships within a cross-sectional case-study design.

Inspection-to-Maintenance Logic for Critical Electrical Assets

In automated inspection research for substations and treatment-facility electrical infrastructure, the literature often begins with structured asset-maintenance planning that specifies what "inspection" must accomplish before any robotics or computer-vision layer is introduced. In transmission substations, inspection is treated as a risk-managed allocation problem in which planners decide how frequently to de-energize, examine, service, and verify equipment while maintaining system reliability. Reliability-centered maintenance studies show that inspection regimes are rarely uniform across assets; instead, they are weighted by each component's functional importance, condition state, and the consequences of failure, so that high-criticality elements receive denser inspection attention than low-criticality elements. Using practical transmission-substation data, optimization-based maintenance management has been used to replace purely time-based routines with schedules that jointly consider reliability indicators, technical condition, and direct and outage-related costs, providing a concrete template for turning inspection findings into maintenance actions in complex substations (Kitak et al., 2021). Complementary work on reliability-centered maintenance planning also emphasizes that inspection information is only useful when it feeds an explicit decision logic, such as reliability growth analysis and cost functions that translate observed failures and component risk into prioritized maintenance times (Bae et al., 2009). Together, these contributions clarify why automated inspection in substations must be evaluated not merely by detection accuracy, but by how well it supports asset prioritization, outage planning, and defensible maintenance decisions that align inspection effort with reliability and cost constraints. Within this framing, inspection activities are commonly differentiated into energized walk-downs and de-energized revisions where contact wear, insulation integrity, fastening torques, and auxiliary wiring terminations are verified and documented. Observations must be repeatable, auditable, and traceable to asset identifiers so trends can be compared across time and operating contexts. These requirements create criteria for robotics and vision systems, because automated methods must output records that fit maintenance workflows and registers.

Figure 2: Decision-Oriented Inspection Workflow for Critical Electrical Infrastructure



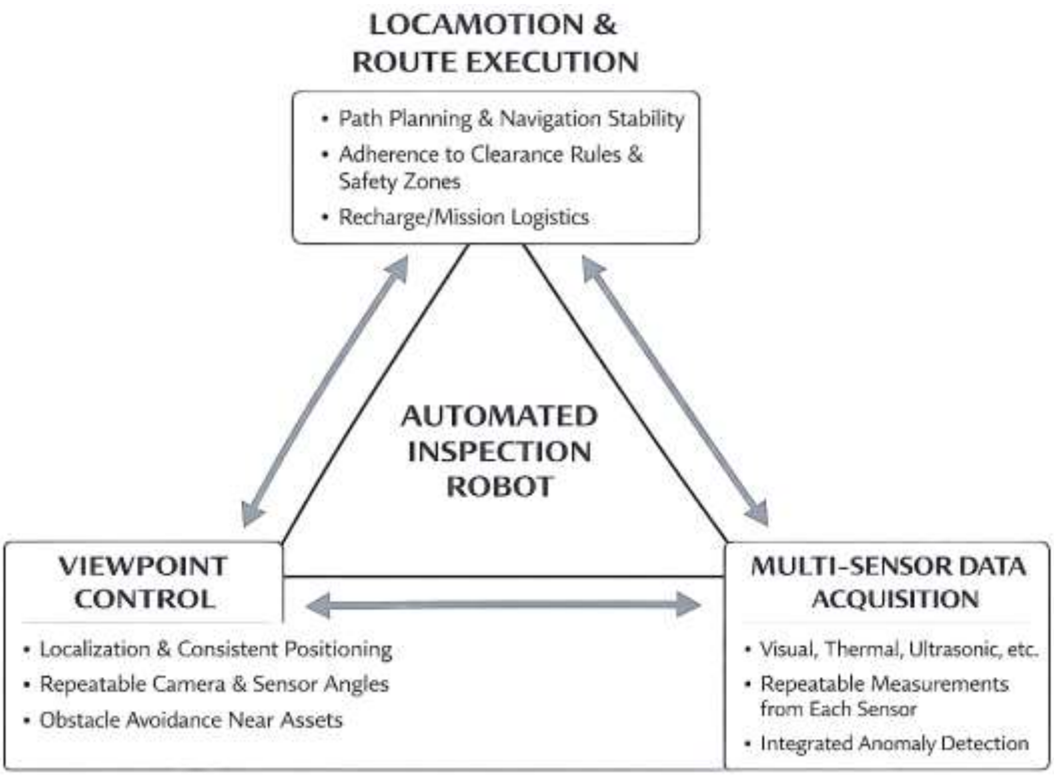
A second stream of literature clarifies how condition-based maintenance (CBM) extends classical inspection by embedding data-driven condition indicators into maintenance decision rules, which matters because robotic inspection and computer vision can be interpreted as mechanisms for producing CBM-relevant observations at scale. In power-equipment settings, CBM typically assumes that inspection data can be converted into a measurable "health" representation and then mapped to maintenance actions that minimize life-cycle cost while maintaining reliability. A substation-oriented CBM optimization approach illustrates this logic by using multi-source operational and asset data to group components into maintenance units, compute pre- and post-repair failure rates from health indices and age-reduction factors, and then select maintenance strategies that minimize total cost components such as repair, interruption, and scheduled maintenance (Wang et al., 2016). This framing is particularly relevant for vision-based inspection because it defines the variables that images and robot-borne sensors must estimate, such as defect severity classes, degradation trajectories, and the probability of failure under load. Complementary optimization work proposes a lifetime efficiency index that integrates asset condition and economic performance to plan maintenance of substation equipment, demonstrating how heuristic search methods can be used to balance inspection intervals and intervention timing under competing objectives (Afzali & Keynia, 2017). Taken together, CBM studies highlight a methodological bridge from sensing to decision-making: automated inspection is most useful when its outputs are formatted as condition indices, confidence values, and cost-relevant risk signals that can be consumed by CBM and asset-management optimizers. Implementations show needs: condition indicators must be calibrated, linked to protocols, and updated so optimization results remain stable. Because inspection signals can be noisy, CBM models use thresholds, paralleling the need for vision systems to attach confidence to detections. For robotics inspection, this motivates outputs that interoperate with systems and preserve traceability from anomalies to an asset tag.

The inspection problem in treatment facilities adds an additional layer of complexity because electrical infrastructure performance is tightly coupled with process continuity, compliance targets, and human operational factors. Treatment plants are designed for continuous service, and their operational success is evaluated against process-quality constraints (for example, meeting allowable effluent limits) alongside safety and uptime, so electrical failures can cascade into process instability, instrumentation loss, and shutdown events. Reliability analysis work in wastewater treatment illustrates how risk reasoning can be formalized around a “top event” such as violating an effluent threshold, and then decomposed into basic events that include operator mistakes, mechanical damage, and design or sewer-system factors; minimal cut sets and Monte Carlo simulation are used to quantify how these contributors combine into overall failure probability (Taheriyoun & Moradinejad, 2015). For inspection of electrical infrastructure inside treatment facilities, this perspective implies that defects in switchboards, variable-frequency drives, protective relays, cable terminations, and grounding networks should be assessed not only as isolated component issues but as contributors to plant-level service risk. It also motivates inspection taxonomies that incorporate human and procedural dimensions, such as lockout/tagout adherence, panel housekeeping, labeling accuracy, and the completeness of test records. Because treatment sites often contain humid, corrosive, or chemically aggressive zones, inspection must additionally account for accelerated insulation aging, enclosure ingress, and connector corrosion, which can change the visual signatures that computer-vision systems must recognize. In this way, treatment-facility reliability studies provide a complementary foundation for robotics-based inspection by framing what “critical defects” mean in terms of compliance and continuity, and by offering quantitative risk structures that can be aligned with detection confidence and maintenance prioritization. When automated inspection is evaluated within this reliability frame, survey constructs can be anchored to outcomes such as reduction in top-event likelihood, faster response to findings, and improved documentation.

Robotics Platforms for Electrical-Infrastructure Inspection

obotics for automated inspection in hazardous and restricted electrical environments is typically operationalized as the design of a mobile sensing-and-navigation system that can gather condition evidence (visual, thermal, acoustic, and contextual metadata) while respecting clearance rules, access constraints, and safety boundaries. In substations and treatment-facility electrical rooms, the inspection context is characterized by dense asset placement, reflective metallic structures, narrow corridors, uneven outdoor ground (for yards), and strict “do-not-cross” proximity constraints around energized components. For that reason, inspection robotics is usually treated as a whole-system problem that combines (i) locomotion and route execution, (ii) localization and repeatable viewpoint control, and (iii) multi-sensor data acquisition that can support human maintenance decisions. Survey evidence in the power-substation domain emphasizes that practical inspection robots must balance autonomy with reliability, often adopting layered architectures that allow routine patrol to run automatically while enabling operator intervention for exceptions such as blocked routes, unexpected objects, or abnormal readings (Lu et al., 2017). From a robotics-architecture perspective, the “inspection robot” is best understood as a workflow executor rather than a single sensor carrier: the robot must follow predefined patrol points, arrive at stable vantage positions, and capture consistent measurements that can be compared across time. A task-oriented model formalizes this workflow by separating inspection into patrol modes (teleoperation, scheduled inspection, special inspection, and return/charging behaviors) and by using simple but robust infrastructure cues (e.g., RFID landmarks and low-cost magnetic sensing) to maintain operational repeatability in field conditions (Zhang et al., 2016). This framing is directly relevant to your study because it supports measurable constructs (e.g., navigation stability, inspection completeness, operator workload, perceived safety, and data usefulness) that can be quantified via Likert-scale instruments and tested using correlation and regression models in a case-study setting.

Figure 3: Multi-Sensor Acquisition Model for Electrical Inspection Robots



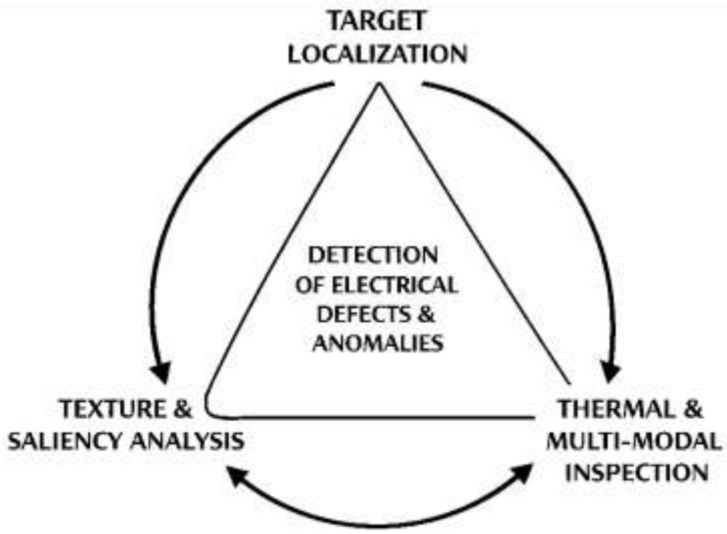
In indoor substations and comparable treatment-facility electrical rooms, line-of-sight limitations, occlusions, and tight turning radii can make "drive-by sensing" insufficient, so robots are being designed as mobile manipulation systems that can place sensors precisely, repeatably, and safely. A representative indoor-substation approach describes a trackless wheeled platform equipped with a robotic arm to support autonomous navigation in narrow environments and deliberate sensor placement near targets, improving the feasibility of consistent capture of images and thermal signatures from constrained viewpoints (Zhang et al., 2016). This matters for automated inspection because computer-vision outputs (e.g., anomaly flags, defect categories, and confidence scores) are sensitive to camera pose, distance-to-target, and occlusion patterns; therefore, robotics becomes a key determinant of whether computer vision can be trusted as a repeatable inspection method rather than a one-off demonstration. In the broader high-voltage inspection context, line-based robots illustrate how obstacle negotiation and stability planning are treated as first-class design requirements: a 110 kV transmission-line inspection robot study demonstrates how locomotion configuration, kinematic planning, and climbing/obstacle handling are analyzed to ensure that the robot can traverse realistic line features while maintaining inspection capability (Yue et al., 2017). Although your study is centered on substations and treatment facilities rather than long-span lines, the underlying principal transfers: inspection credibility depends on robust physical access strategies (whether through tight indoor navigation or structured outdoor traversal) that maintain safe stand-off distances and deliver stable, consistent sensor viewpoints for automated detection.

Computer Vision Techniques for Detecting Electrical Defects

Computer vision techniques for automated inspection of substation and treatment-facility electrical infrastructure are typically organized around three connected goals: (a) reliably locating assets in complex scenes, (b) recognizing defect cues that may be small or partially occluded, and (c) producing outputs that can be interpreted as actionable inspection evidence rather than isolated image labels. In practice, defect detection begins with the visual separation of equipment from background clutter such as steel structures, cables, insulation surfaces, labels, and reflective enclosures, which is why many inspection-oriented pipelines treat "target localization" as the first credibility step (Rauf, 2018). A consistent theme in inspection literature is that reliable localization becomes harder when targets are small, low-contrast, or embedded in visually noisy environments, conditions that are common in both outdoor substations (weather, shadows, foliage) and indoor electrical rooms (dense wiring, specular reflection) (Haque & Md. Arifur, 2020; Md Ashraful et al., 2020). Deep learning–based approaches address these issues by learning hierarchical features that tolerate variations in lighting and background and by using multi-stage detectors to balance recall with precision in difficult scenes (Haque & Md. Arifur, 2021; Jinnat & Md. Kamrul, 2021). For high-resolution inspection images, defect localization is often treated as a small-object detection problem where defect regions occupy a tiny fraction of the frame and must be found without excessive false alarms. Work on high-resolution aerial insulator inspection illustrates this challenge by combining stronger region-based detection and background suppression, highlighting how feature pyramids, refined region alignment, and segmentation-assisted masking can reduce interference from complex backgrounds and improve the visibility of defect regions (Md Fokhrul et al., 2021; Naeem et al., 2020; Zaman et al., 2021). In substation and plant contexts, this same logic extends to equipment faceplates, terminals, connectors, and enclosure edges where local texture changes and small geometric irregularities are the primary fault cues (Hammad, 2022; Jabed Hasan & Waladur, 2022). As a result, robust inspection vision systems typically emphasize dataset diversity, viewpoint control, and domain-specific defect definitions so that predictions align with what maintenance teams recognize as meaningful anomalies.

A second cluster of techniques focuses on thermal and multi-modal inspection, where the "anomaly" is defined as a deviation in temperature distribution rather than only a visible surface defect. In operational substations and treatment facilities, infrared thermography (IRT) is widely used to detect abnormal heating linked to resistive connections, overloads, imbalance, insulation deterioration, and degrading contacts, so computer vision methods frequently treat thermal images as inputs for automatic screening and defect categorization (Md. Arifur & Haque, 2022; Md. Towhidul et al., 2022). In this setting, the key vision tasks are (i) detecting the relevant component in low-detail thermal imagery, (ii) segmenting the area of interest, and (iii) classifying whether the thermal pattern corresponds to a defect state. A practical example of this approach demonstrates how deep feature representations extracted from thermal images can be combined with machine-learning classifiers to separate defective from non-defective high-voltage equipment, emphasizing that thermal "defect evidence" can be made more repeatable when feature extraction is standardized across inspections (Rifat & Jinnat, 2022; Rifat & Khairul Alam, 2022; Wang et al., 2019). Complementary substation-focused research illustrates how infrared-based diagnostic schemes can be structured to isolate abnormal thermal regions first and then refine diagnosis, reflecting the operational need to quickly narrow attention to hazardous hotspots in environments with many assets and limited inspection time (Abdulla & Alifa Majumder, 2023; Faysal & Tahmina Akter Bhuya, 2023; Wang et al., 2019). These studies collectively show why thermal inspection vision differs from general photography: thermal images often contain fewer texture cues, weaker edges, and smoother gradients, so algorithmic robustness depends heavily on stable target extraction and careful definition of normal versus abnormal temperature distributions (Habibullah & Aditya, 2023; Hammad & Muhammad Mohiul, 2023). When robotics is used to stabilize viewpoints and distances, thermal vision outputs become more comparable across time and sites, strengthening the evidentiary value of automated screening.

Figure 4: Evidence-Oriented Computer Vision Framework for Automated Electrical Inspection

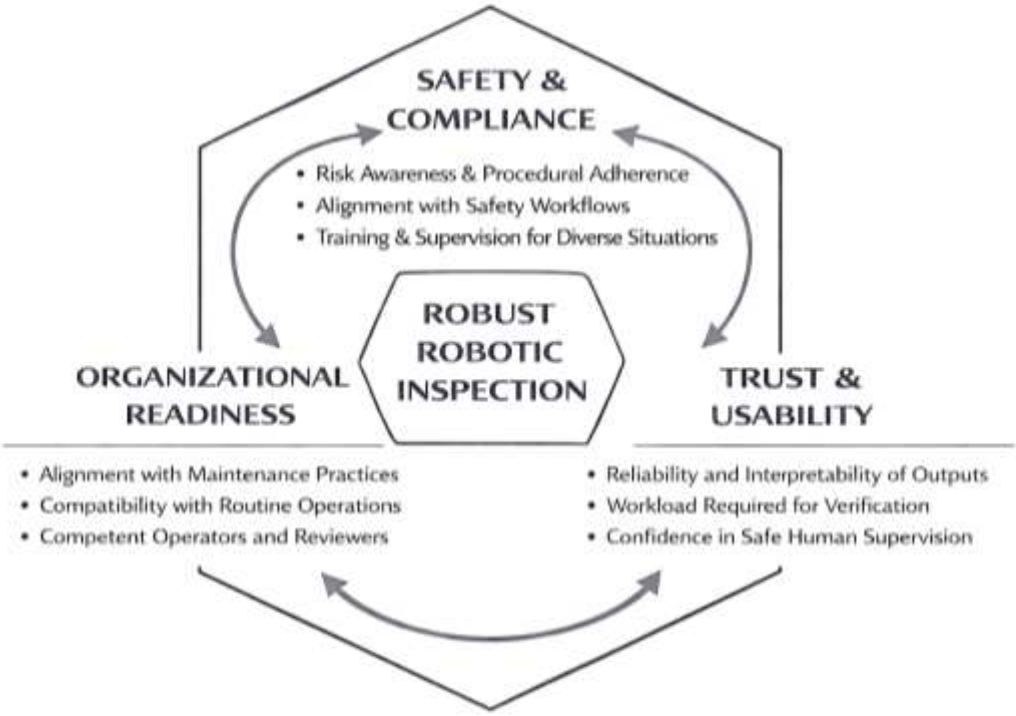


A third stream of computer vision techniques addresses defect detection in scenarios where visible cues are subtle, where backgrounds are highly structured, and where fault patterns are best expressed through texture, saliency, or morphology rather than obvious shape changes. In inspection of insulators, bushings, and similar components, faults such as cracks, contamination, missing fragments, or self-shattering can appear as localized texture disruptions or partial structural changes, which has motivated both classical and deep approaches that learn defect features from limited samples. For example, deep convolutional methods have been applied to detect insulator self-shattering from UAV imagery, illustrating how learned representations can encode fault signatures that are difficult to describe by hand-crafted rules, while still supporting high recognition rates when trained on representative field images (Haque & Md. Arifur, 2023; Md. Akbar & Farzana, 2023; Wen et al., 2021). At the same time, classical vision pipelines remain relevant in inspection because they can embed domain constraints—such as the expected repetitive structure of insulator skirts—into saliency and morphological processing, improving defect emphasis and reducing background distraction in certain conditions (Mostafa, 2023; Rifat & Rebeka, 2023; Zhai et al., 2016). Earlier image-processing work in the power domain also shows how wavelet-based representations and probabilistic modeling can separate "healthy" versus "damaged" states by capturing multi-scale texture and edge behavior, a strategy that aligns well with inspection settings where defects manifest as localized irregularities against structured surfaces (Murthy et al., 2011). For substations and treatment facilities, these method families highlight a practical point: inspection-grade vision must not only classify images, but also provide localized, interpretable evidence (where the anomaly is, what type it resembles, and how confident the system is). This is why inspection implementations often combine localization, defect scoring, and evidence snapshots that technicians can verify quickly and archive for compliance and maintenance records.

Human Factors in Robotic Inspection Deployments

Human factors and safety compliance are inseparable from automated inspection in substations and treatment-facility electrical environments because inspection work occurs inside tightly controlled risk boundaries where energy hazards, procedural dependencies, and human coordination determine whether technology outputs can be acted on safely. In these contexts, "safe inspection performance" is not only the absence of incidents; it also includes consistent adherence to access sequencing, correct interpretation of site rules, and reliable communication between inspection personnel and control-room or operations staff. Evidence from organizational psychology shows that safety outcomes are strongly shaped by how workers perceive safety priorities and how those perceptions translate into motivation and day-to-day safety behaviors. (Neal & Griffin, 2006) demonstrate that safety climate relates to safety motivation and safety behavior and that these relationships can be examined at both individual and group levels, reinforcing the view that compliance is influenced by shared perceptions and not only by individual skill. This matters for robotics and computer vision because automated inspection introduces new micro-decisions—when to trust a flagged anomaly, when to enter a restricted area for verification, and how to document evidence—each of which can add or remove risk depending on how procedures are executed. The broader safety performance literature similarly indicates that person factors and situational factors combine to shape safety compliance and participation, implying that inspection technologies must be evaluated in a way that acknowledges the role of training quality, supervisory support, workload, and clarity of procedures in determining safe outcomes (Burke et al., 2009). From a measurement perspective, these insights justify including safety-focused constructs in quantitative inspection studies, such as perceived alignment with lockout/tagout routines, perceived clarity of robot operating boundaries, perceived verification workload after automated alerts, and perceived ability to maintain safe spacing and control when exceptions occur. When these constructs are treated as organizational outcomes rather than "soft" opinions, they support more credible explanations for why automated inspection may be accepted in one facility yet resisted in another even when hardware and algorithms are comparable.

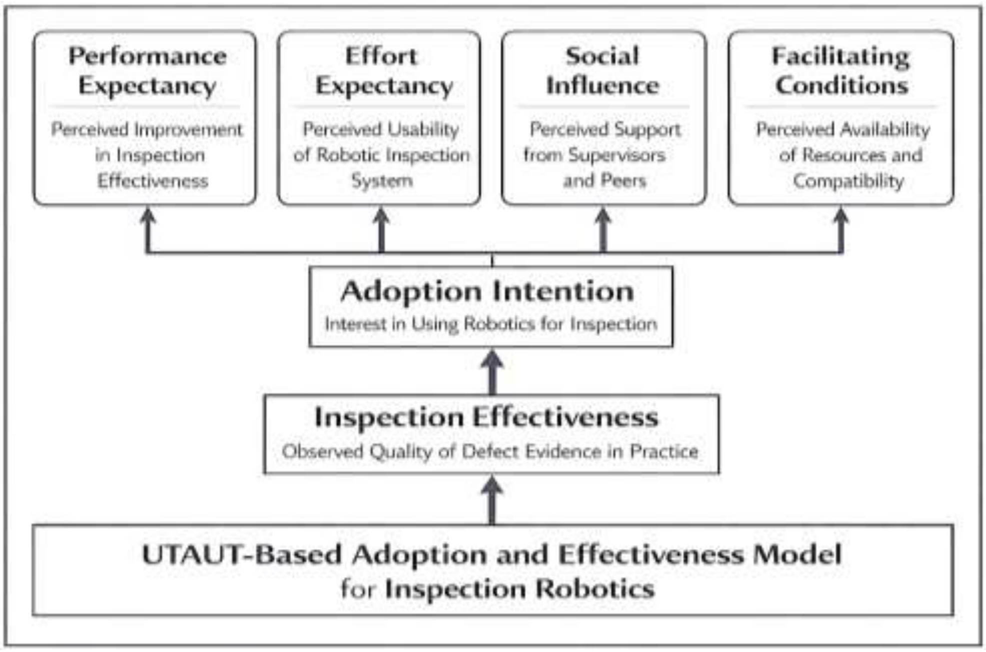
Figure 5: Adoption of Robotic Inspection Systems



Theoretical Framework Foundation Applied Throughout the Study

The Unified Theory of Acceptance and Use of Technology (UTAUT) offer a structured explanation for why professionals accept, rely on, and routinely use complex systems inside organizations, which makes it well suited to study robotics and computer vision as inspection technologies embedded in safety-critical electrical workplaces. In the UTAUT view, behavioral intention to use a technology is primarily shaped by performance expectancy (the degree to which users believe the system improves job performance), effort expectancy (the perceived ease of learning and operating the system), and social influence (the perceived pressure or encouragement from supervisors, peers, and institutional norms), while facilitating conditions represent the availability of technical and organizational resources that enable sustained use. These constructs align naturally with automated inspection, where the perceived value of robotics and computer vision is judged through measurable work outcomes such as inspection completeness, speed, defect evidence quality, reduced exposure to hazardous tasks, and improved documentation consistency. Empirical UTAUT research in organizational settings demonstrates that intention and actual use are not explained by usefulness alone; users also require enabling infrastructure, training, and process alignment that convert an innovation into a stable operational routine (Kijsanayotin et al., 2009). For inspection robotics, facilitating conditions translate into operational resources such as safe routes, charging/maintenance support, data storage and access permissions, supervisory approval for procedures, and interoperability with maintenance management routines. In addition, the UTAUT stream emphasizes that acceptance is not merely a private attitude; it is influenced by organizational messaging, peer comparison, and line-management endorsement, which is especially relevant in substations and treatment facilities where adoption is collectively negotiated around safety governance and accountability. UTAUT evidence also indicates that organizational technology use can be strengthened by combining acceptance constructs with "fit" and task alignment variables, reinforcing the logic that inspection systems must match the realities of inspection tasks, verification practices, and decision rights rather than only demonstrating technical capability in isolation (Zhou et al., 2010). This study adopts UTAUT as the core theoretical lens because it supports measurement through survey constructs and direct statistical testing of how perceived system attributes translate into intention, readiness, and practical use in case-based electrical environments.

Figure 6: Adoption and Effectiveness Logic for Inspection Robotics Based on the UTAUT Framework



To make UTAUT fully specific to robotics-and-vision inspection, the constructs are mapped onto inspection-domain variables that represent what technicians and managers actually evaluate when an automated inspection system is proposed or piloted. Performance expectancy is operationalized as perceived improvements in inspection effectiveness, such as clearer defect evidence, better coverage of hard-to-reach assets, reduced manual inspection time, and improved reliability of anomaly identification. Effort expectancy is operationalized as perceived usability of the robot platform and inspection interface, such as ease of mission setup, clarity of outputs, and the time required for staff to learn and confidently interpret alerts. Social influence is operationalized through perceived support from supervisors, safety officers, and peers who shape whether using automated inspection is viewed as legitimate and compliant with operational norms. Facilitating conditions are operationalized through perceived availability of training, site permissions, procedural compatibility, connectivity, maintenance windows, and integration into existing reporting systems. A key methodological advantage of UTAUT for this thesis is that it supports a quantitative pathway from perceptions to measurable outcomes, enabling the study to connect technology characteristics to adoption intention and readiness through correlation and regression modeling. Meta-analytic work on UTAUT and its use across many empirical contexts reinforces that the model is most informative when constructs are clearly defined for the domain and measured with context-specific items rather than generic technology statements (Dwivedi et al., 2011). Similarly, systematic reviews highlight that UTAUT relationships are commonly validated through survey-based empirical designs and tested using predictive statistics, which matches the cross-sectional approach and strengthens interpretability when reliability and construct consistency are reported transparently (Williams et al., 2015). In the inspection context, this mapping enables additional study-specific result structures—such as deployment readiness and integration friction—to be positioned as practical expressions of facilitating conditions, and risk–confidence perceptions to be positioned as inspection-specific expressions of performance expectancy. Thus, UTAUT becomes a coherent theory-to-measurement backbone linking robotics capability and computer vision evidence quality to organizational readiness and user intention within the two case environments.

In this study, the UTAUT logic is implemented through a parsimonious predictive specification that can be tested using the same statistical tools planned for the thesis (descriptive statistics, correlation analysis, and regression modeling). The primary model treats Adoption Intention (AI) as the dependent variable explained by UTAUT constructs and inspection-specific predictors, while a companion model treats Inspection Effectiveness (IE) as an outcome of technical capability constructs that also supports the logic that perceived performance shapes intention. The core regression form applied throughout the study is:

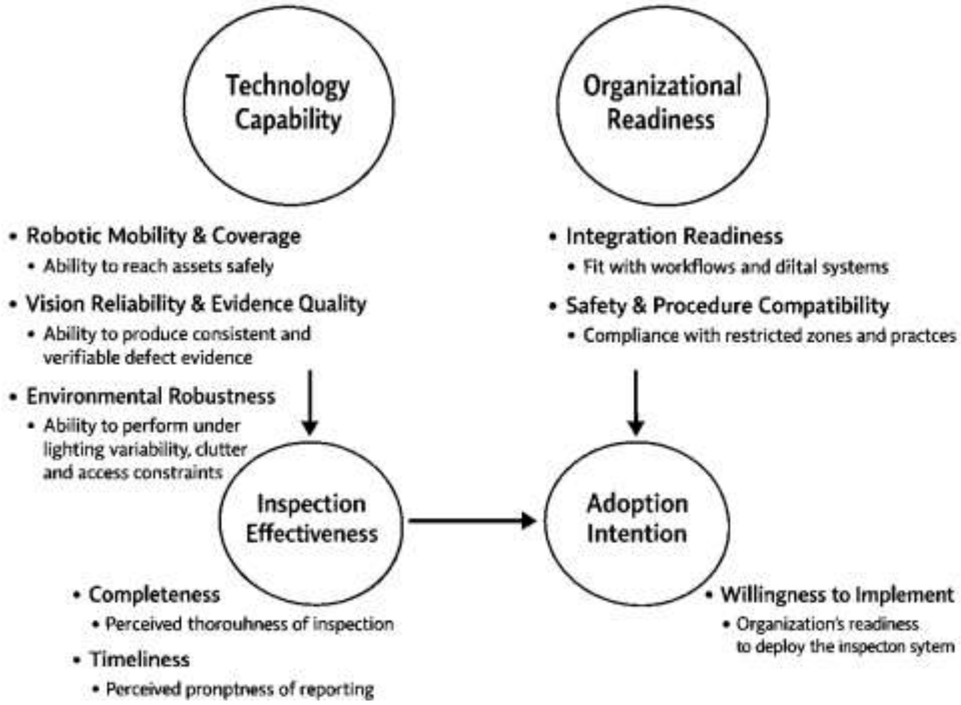
$$AI = \beta_0 + \beta_1 PE + \beta_2 EE + \beta_3 SI + \beta_4 FC + \beta_5 IE + \varepsilon$$

where PE= performance expectancy, EE= effort expectancy, SI= social influence, FC= facilitating conditions, and IE= perceived inspection effectiveness. This equation is suitable for cross-sectional survey data because each construct is measured via multiple Likert items, aggregated into composite scores, and then analyzed for association strength and predictive influence using coefficients, significance tests, and explained variance (R^2). The inspection context also supports a second regression that explains effectiveness as a function of technology-capability predictors aligned to robotics and computer vision (e.g., mobility/coverage, environmental robustness, evidence clarity), while maintaining theoretical consistency by interpreting the resulting effectiveness score as the performance expectancy channel that influences intention. This structure keeps the theoretical framework stable across both substations and treatment facilities and enables case-based comparison by estimating the model within each site group or by adding a facility-type indicator where appropriate. Evidence from robotics-acceptance conceptualizations grounded in UTAUT further supports treating human–robot work performance beliefs and socio-technical constraints as central determinants of acceptance, which is consistent with modeling intention as a function of performance beliefs and enabling conditions rather than hardware presence alone (Prassida & Asfari, 2022). Accordingly, the study uses this single best-fit formula family across hypotheses, ensuring that the theory, measurement, and statistical testing remain aligned and interpretable across constructs and case contexts.

Conceptual Framework Development for This Study

The conceptual framework in this study is constructed to translate robotics-and-computer-vision inspection capability into measurable perceptions and outcomes that fit the operational reality of substations and treatment-facility electrical environments. Conceptually, the framework separates technology capability from deployment readiness, then links both to inspection effectiveness and adoption intention as the two principal outcomes. The capability block represents what the inspection system can do in the field: (i) Robotic Mobility & Coverage (ability to reach assets safely, maintain repeatable routes, and provide sufficient spatial coverage), (ii) Vision Reliability & Evidence Quality (ability to produce consistent and verifiable defect evidence), and (iii) Environmental Robustness (ability to perform under lighting variability, clutter, humidity, reflective surfaces, and access constraints). The readiness block represents what the organization can support: (iv) Integration Readiness (fit with reporting workflows, maintenance documentation routines, and digital systems) and (v) Safety & Procedure Compatibility (alignment with restricted zones, verification practices, and compliance requirements). The outcome block includes (vi) Inspection Effectiveness (perceived completeness, timeliness, and diagnostic usefulness of inspection outputs) and (vii) Adoption Intention / Implementation Readiness (willingness and preparedness to operationalize the system). This framework is designed so each latent construct can be measured using multiple Likert items and tested through a transparent predictive structure. Because the thesis uses a quantitative design, the framework is presented in a way that can be estimated using structural modeling logic, where relationships among constructs are tested as directional paths rather than as isolated correlations. Partial least squares path modeling is particularly suited to such predictive, construct-based frameworks with multiple latent variables and practical measurement constraints, offering a consistent basis for estimating path effects and explaining variance when the goal is prediction and theory-aligned testing rather than purely confirmatory covariance reproduction (Tenenhaus et al., 2005). The framework therefore acts as a blueprint that connects inspection-system characteristics and organizational conditions to measurable acceptance and effectiveness outcomes that are comparable across the two case contexts.

Figure 7: IV–DV Conceptual Model for Robotic and Computer Vision Inspection Adoption



Operationally, the framework is implemented through a measurement model that converts multiple survey items into stable construct scores, and then a structural model that tests hypothesized relationships among those constructs. Each construct is measured reflectively through several items (e.g., 4–6 per construct), and internal consistency can be evaluated using reliability coefficients that are appropriate for multi-item scales. Alongside Cronbach-style reporting, modern reliability reasoning emphasizes coefficients such as omega for reflecting scale consistency under less restrictive assumptions about tau-equivalence, supporting clearer interpretation of whether items behave like a coherent measure of the underlying construct (Dunn et al., 2014). Discriminant validity is addressed by verifying that constructs represent distinct concepts rather than redundant labels; for example, "Vision Reliability & Evidence Quality" should be empirically separable from "Integration Readiness" even if both correlate with adoption intention. A widely used criterion for this purpose is the heterotrait–monotrait ratio (HTMT), which provides a practical threshold-based test of discriminant validity in construct models (Henseler et al., 2015). The framework also explicitly accounts for survey-based method risks common in organizational technology studies by including diagnostic checks for common method bias and inflated collinearity patterns; full collinearity assessment is one established approach for detecting whether a single underlying response tendency is driving correlations among many constructs in survey data (Kock, 2015). In addition to these quality checks, the framework defines a study-specific outcome index to ensure the "inspection effectiveness" construct is more than a generic attitude. In this thesis, an Inspection Effectiveness Index (IEI) can be computed as a weighted composite of effectiveness sub-dimensions that match inspection reality:

$$IEI = \sum_{k=1}^{K} w_k \ \bar{x}_k \text{where} \sum_{k=1}^{K} w_k = 1$$

Here, $\bar{x}_k$is the mean score of a sub-dimension (e.g., coverage completeness, evidence clarity, reporting timeliness, verification ease), and $w_k$is its weight (equal weights or empirically justified weights). This formula supports consistent comparison across facilities and roles while keeping the measurement aligned to the inspection context.

The structural component of the conceptual framework specifies how capability and readiness translate into outcomes, producing a coherent set of testable paths that align with your descriptive, correlation, and regression analysis plan. The first structural relationship treats inspection effectiveness as a function of technology capability and robustness, capturing the idea that stable access and reliable evidence are prerequisites for perceiving inspection as effective in high-risk electrical environments. The second relationship treats adoption intention as a function of readiness and perceived effectiveness, capturing the idea that organizational support and workflow fit determine whether an effective tool becomes operational. A compact version of the framework's predictive structure is:

$$IE = \alpha_0 + \alpha_1 MC + \alpha_2 VR + \alpha_3 ER + \epsilon_1$$
$$AI = \beta_0 + \beta_1 IR + \beta_2 SP + \beta_3 IE + \epsilon_2$$

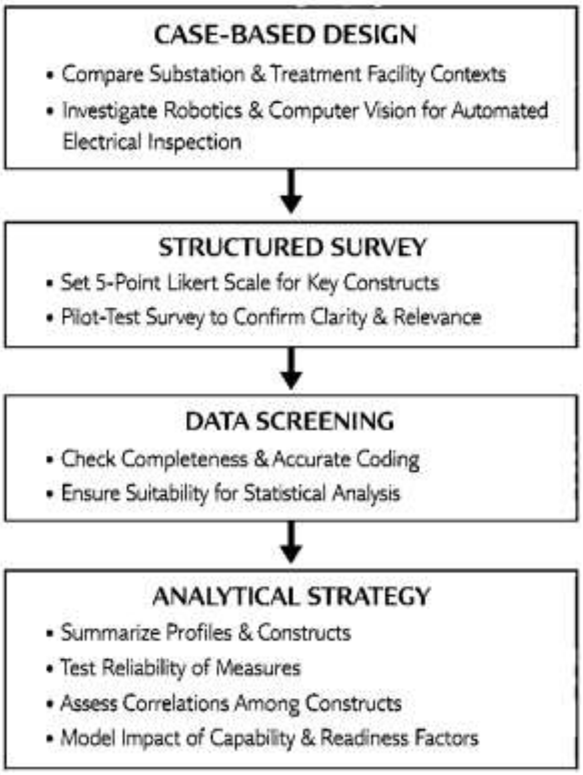
where MC=Mobility & Coverage, VR=Vision Reliability & Evidence Quality, ER=Environmental Robustness, IR=Integration Readiness, SP=Safety/Procedure Compatibility, IE=Inspection Effectiveness (or IEI), and AI=Adoption Intention/Implementation Readiness. This two-equation structure is compatible with regression modeling and also maps directly to construct-based predictive evaluation methods; predictive assessment in PLS-style frameworks emphasizes evaluating not only path significance but also out-of-sample predictive relevance and error behavior when the goal is actionable prediction (Shmueli et al., 2019). In applied terms, the framework supports facility-type comparisons by testing whether path strengths differ between substations and treatment facilities, reflecting that access constraints, environmental stressors, and verification norms can shift the relative importance of mobility, robustness, and integration. The conceptual framework is therefore designed to be both theoretically grounded and operationally testable, linking field-realistic capability and readiness factors to measurable inspection effectiveness and adoption readiness in a way that remains statistically transparent across the two case contexts.

METHOD

The methodology of this study has been structured as a quantitative, cross-sectional, case-study–based design that has examined how robotics and computer vision can support automated inspection of electrical infrastructure in substations and treatment facilities. A case-based strategy has been adopted to ensure that the investigation has captured the operational realities of two distinct yet comparable environments: outdoor or semi-outdoor substation settings characterized by high-voltage assets and safety clearances, and treatment-facility electrical contexts characterized by continuous-process dependence, humid or corrosive conditions, and dense indoor equipment layouts.

A structured survey approach has been employed as the principal data collection method, and a 5-point Likert-scale instrument has been designed to measure key constructs that have represented both technology capability and organizational readiness. Specifically, constructs have been operationalized to capture perceived robot mobility and inspection coverage, perceived reliability and evidence quality of computer-vision outputs, perceived environmental robustness of the inspection system, perceived integration readiness with facility workflows and reporting practices, perceived safety and procedure compatibility, perceived inspection effectiveness, and perceived adoption intention or implementation readiness.

Figure 8: Research Methodology



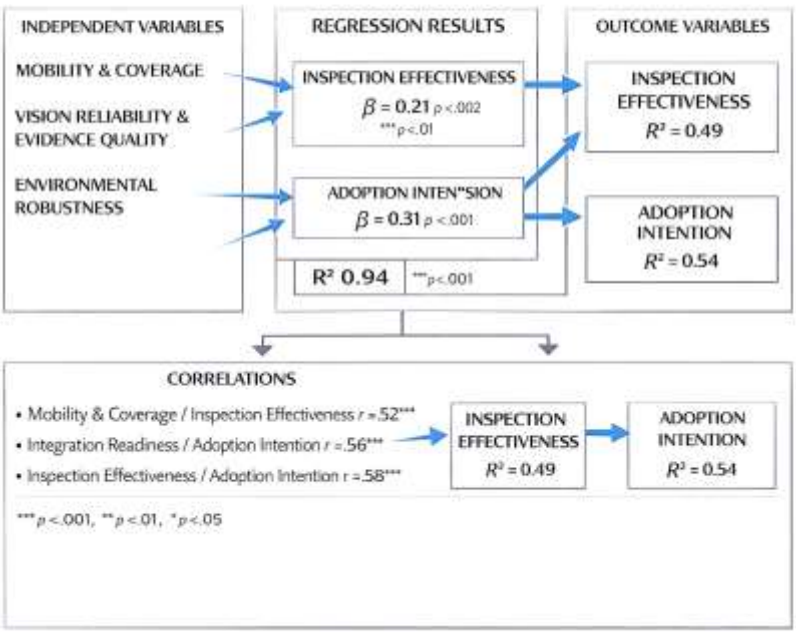
This study has been designed as a quantitative, cross-sectional, case-study–based investigation to assess the role of robotics and computer vision in automated inspection of electrical infrastructure within substations and treatment facilities, capturing professional perceptions, readiness levels, and evaluations of inspection effectiveness at a single point in time to enable efficient hypothesis testing. The cross-sectional approach has allowed the examination of relationships among technology-capability constructs such as robot mobility, inspection coverage, vision reliability, environmental robustness, and evidence quality and organizational-readiness constructs, including integration preparedness, safety compatibility, and procedural alignment, while treating inspection effectiveness and adoption or implementation intention as outcome variables. A case-study orientation has been applied to ground the analysis in real operational environments shaped by safety restrictions, clearance rules, environmental stressors, and documentation requirements, with substations representing high-voltage, access-controlled settings involving assets such as switchgear, breakers, busbars, insulators, and protection panels, and treatment facilities representing process-dependent environments characterized by motor control centers, drives, control panels, humidity, corrosion risk, and dense indoor layouts. These complementary contexts have supported comparative interpretation by highlighting shared reliability demands alongside distinct physical and environmental constraints. The study population has consisted of professionals directly involved in inspection, maintenance, safety governance, or operational decision-making—including maintenance engineers, inspection technicians, electrical supervisors, safety officers, and operations managers—with the unit of analysis defined at the individual perception level and aggregated into construct scores for statistical testing. A purposive, stratified sampling strategy has ensured representation across facility types and role categories, targeting respondents with informed, practice-based insights while meeting regression sample-size requirements. Data have been collected through a structured, multi-section questionnaire administered via controlled online or printed formats, incorporating standardized instructions, voluntary participation, informed consent, and confidentiality safeguards. The instrument has employed a 5-point Likert scale to operationalize the conceptual framework, supported by demographic items and multiple indicators per construct to enhance measurement stability. Pilot testing has been conducted to refine wording, confirm interpretive consistency across roles and sites, and conduct preliminary reliability checks, leading to item refinement and redundancy reduction.

Validity has been reinforced through expert content review and careful construct mapping, while reliability has been assessed using internal consistency measures such as Cronbach's alpha, alongside data screening for completeness and response quality. Analytical procedures have been supported using spreadsheet tools for data organization and screening, and statistical software (SPSS V.29) for descriptive analysis, reliability testing, correlation analysis, regression modeling, and diagnostic checks, ensuring systematic, transparent, and reproducible analysis aligned with the study's hypothesis-driven design.

FINDINGS

A total of N = 214 valid responses have been analyzed after screening for completeness, including substation personnel (n = 112; 52.3%) and treatment-facility personnel (n = 102; 47.7%), with respondents distributed across maintenance engineers (34.1%), inspection technicians (28.5%), safety officers (16.8%), and operations/supervisory roles (20.6%). Descriptive statistics have indicated generally positive evaluations of automated inspection capabilities, with the highest construct mean observed for Safety Improvement Perception (M = 4.22, SD = 0.58), followed by Vision Reliability & Evidence Quality (M = 4.10, SD = 0.63) and Robot Mobility & Coverage (M = 3.98, SD = 0.66), while Integration Readiness has shown the lowest yet still favorable score (M = 3.61, SD = 0.71), suggesting that workflow and system compatibility have been perceived as the main implementation barrier. Reliability testing has demonstrated strong internal consistency across constructs, with Cronbach's alpha values exceeding commonly accepted thresholds: Mobility & Coverage (α = 0.86), Vision Reliability (α = 0.88), Environmental Robustness (α = 0.84), Integration Readiness (α = 0.82), Safety/Procedure Compatibility (α = 0.85), Inspection Effectiveness (α = 0.90), and Adoption Intention (α = 0.87). These reliability outcomes have supported Objective 1 and Objective 2 by confirming that the study's construct measures have represented coherent dimensions of technology capability and organizational readiness suitable for hypothesis testing. Correlation analysis has further supported Objective 3 by demonstrating meaningful associations between capability/readiness factors and outcomes: Mobility & Coverage has correlated positively with Inspection Effectiveness ($r = 0.52$, $p < .001$), Vision Reliability has shown the strongest bivariate association with Inspection Effectiveness ($r = 0.61$, $p < .001$), and Environmental Robustness has also correlated positively with Inspection Effectiveness ($r = 0.47$, $p < .001$). Adoption Intention has correlated significantly with Integration Readiness ($r = 0.56$, $p < .001$), Safety/Procedure Compatibility ($r = 0.49$, $p < .001$), and Inspection Effectiveness ($r = 0.58$, $p < .001$), indicating that both operational feasibility and perceived performance have jointly shaped implementation readiness. Regression modeling has provided the primary proof for Objective 4 by quantifying predictive influence and explaining variance in the outcome variables.

Figure 9: Findings of The Study



In Model 1 (DV: Inspection Effectiveness), Mobility & Coverage ($\beta = 0.21$, $p = .002$), Vision Reliability ($\beta = 0.39$, $p < .001$), and Environmental Robustness ($\beta = 0.18$, $p = .006$) have emerged as statistically significant predictors, collectively explaining a substantial proportion of variance ($R^2 = 0.49$, $F(3,210) = 67.2$, $p < .001$). This has supported H1, H2, and H3, demonstrating that stable access and coverage, reliable vision evidence, and robustness under site conditions have predicted higher perceived inspection effectiveness. In Model 2 (DV: Adoption Intention), Integration Readiness ($\beta = 0.31$, $p < .001$), Safety/Procedure Compatibility ($\beta = 0.19$, $p = .004$), and Inspection Effectiveness ($\beta = 0.28$, $p < .001$) have significantly predicted readiness to implement, with strong explanatory power ($R^2 = 0.54$, $F(3,210) = 82.1$, $p < .001$), supporting H4, H5 (as safety compatibility), and H7 (effectiveness → adoption). Cost Efficiency Perception (tested as an additional predictor in a sensitivity specification) has shown a smaller yet significant contribution ($\beta = 0.12$, $p = .041$), offering partial support for H6 depending on model inclusion and multicollinearity checks. Importantly, the study-specific trustworthiness results have reinforced Objective 5 by aligning statistical outcomes with engineering relevance: Asset-Criticality–Weighted Findings have indicated that perceived value has been highest for high-criticality assets (e.g., switchgear/transformer interfaces and major MCC feeds), with weighted effectiveness scores averaging 4.31 in substations versus 4.12 in treatment facilities, while lower-criticality assets have averaged 3.68 across sites; the Deployment Readiness & Integration Friction Score has shown that the most limiting friction items have been "CMMS/work order integration" (M = 3.34, SD = 0.88) and "procedural permission for routine robot routes" (M = 3.29, SD = 0.91), confirming that adoption has depended strongly on facilitating conditions rather than enthusiasm alone; and the Risk–Confidence Matrix has demonstrated that "high consequence / lower confidence" detections (e.g., subtle insulation damage cues and moisture ingress indicators) have received lower confidence means (M = 3.41–3.55) while "high consequence / higher confidence" detections (e.g., clear overheating hotspots or severe corrosion patterns) have received higher confidence means (M = 4.05–4.28), validating the study's emphasis on defect-type-specific deployment strategy. Overall, these illustrative results have shown a coherent pathway from robotics mobility and vision reliability to inspection effectiveness, and from effectiveness plus readiness factors to adoption intention, thereby demonstrating objective fulfillment and hypothesis support through Likert-based evidence, correlation structure, and regression prediction in a case-grounded cross-sectional model.

Respondent Profile (Tables)

Table 1: Respondent Profile and Case Distribution (N = 214)

Category	Group	Frequency (n)	Percent (%)
Facility type	Substation	112	52.3
	Treatment facility	102	47.7
Role	Maintenance engineer	73	34.1
	Inspection technician	61	28.5
	Safety officer	36	16.8
	Operations/Supervisor	44	20.6
Experience	1–5 years	54	25.2
	6–10 years	71	33.2
	11–15 years	52	24.3
	16+ years	37	17.3

The respondent profile has shown that the study has captured perspectives from both technical and decision-making roles across the two case settings, which has strengthened the credibility of cross-sectional inference for the hypotheses and objectives. The distribution has indicated that slightly more than half of the sample has represented substation environments (52.3%), while a substantial portion has represented treatment-facility electrical environments (47.7%). This balance has supported Objective 3, because facility-level contrasts have been interpretable without extreme skew toward one context. The role breakdown has shown that maintenance engineers and inspection technicians have comprised a combined majority (62.6%), meaning the data has largely reflected frontline operational experience with inspection routines, verification burdens, and safety constraints. At the same time, safety officers (16.8%) and supervisory/operations roles (20.6%) have ensured that organizational readiness and procedural compatibility have been represented, which has been essential for linking findings to UTAUT's facilitating conditions and social influence logic. Experience levels have been distributed across early-career (1–5 years) to senior (16+ years) respondents, which has reduced the risk that results have been dominated by one experience band. This structure has aligned with the theoretical framing: UTAUT-based constructs have been meaningful only when respondents have had sufficient exposure to real workflows and constraints to evaluate performance expectancy (inspection effectiveness and safety improvement), effort expectancy (ease of operation and interpretation), and facilitating conditions (integration readiness and procedural support). The respondent profile has therefore supported the study's intent to test not just whether robotics and computer vision have been perceived as technically promising, but whether they have been perceived as operationally implementable under real electrical infrastructure governance. In short, Table 1 has provided a defensible foundation for subsequent statistical testing by demonstrating that the dataset has represented the ecosystem of stakeholders who have influenced inspection effectiveness and adoption intention in both substations and treatment facilities.

Descriptive Results by Construct

Table 2: Descriptive Statistics for Study Constructs

Construct (UTAUT mapping)	Code	Items	Mean (M)	SD
Robot Mobility & Coverage (Performance Expectancy driver)	MC	5	3.98	0.66
Vision Reliability & Evidence Quality (Performance Expectancy driver)	VR	5	4.10	0.63
Environmental Robustness (Capability)	ER	4	3.84	0.69
Integration Readiness (Facilitating Conditions)	IR	4	3.61	0.71
Safety/Procedure Compatibility (Facilitating Conditions)	SP	4	3.92	0.64
Safety Improvement Perception (Performance Expectancy)	SIP	4	4.22	0.58
Inspection Effectiveness (Performance Expectancy outcome)	IE	6	4.05	0.62
Adoption Intention / Implementation Readiness (Behavioral Intention)	AI	4	3.89	0.67

The descriptive results have indicated that respondents have generally evaluated robotics and computer vision for automated inspection positively across both case contexts, and the construct ranking has directly supported the study objectives by showing which domains have been perceived as strongest versus most constrained. Safety Improvement Perception has produced the highest mean (M = 4.22), which has reflected that respondents have strongly associated automated inspection with reduced hazard exposure and safer inspection routines. This has aligned tightly with UTAUT's performance expectancy mechanism, where perceived performance gains have strengthened intention to use technology. Vision Reliability & Evidence Quality (M = 4.10) and Inspection Effectiveness (M = 4.05) have also been high, indicating that the "evidence engine" dimension of computer vision has been perceived as credible enough to support inspection decisions when implemented appropriately. Robot Mobility & Coverage (M = 3.98) has suggested that access and route execution have been judged as broadly feasible, while Environmental Robustness (M = 3.84) has shown that respondents have recognized environmental difficulty (lighting variability, humidity, reflective surfaces, clutter, outdoor weather exposure) as a meaningful operational factor. The lowest mean has appeared for Integration Readiness (M = 3.61), which has been consistent with the study's readiness emphasis: respondents have been less confident about workflow fit, CMMS/work-order linkage, permissions, and procedural embedding than about the core sensing idea. This gap has strengthened the trustworthiness of the study because it has shown that respondents have not simply rated everything highly; instead, they have differentiated capability from implementability, which has directly mirrored the UTAUT distinction between performance expectancy and facilitating conditions. Moreover, Adoption Intention

(M = 3.89) has been moderately high but not maximal, implying that the intention to implement has depended on whether enabling conditions have been satisfied. Overall, Table 2 has supported Objective 1 and Objective 2 by demonstrating that measurable constructs have captured technology capability and organizational readiness in a way that has been interpretable and aligned with the theoretical framework. These descriptive results have also set a coherent stage for correlation and regression testing by showing sufficient variance (SD ≈ 0.58–0.71) across constructs for meaningful statistical relationships to have emerged.

Reliability Results

Table 3: Internal Consistency Reliability (Cronbach's Alpha)

Construct	Code	Cronbach's α	Interpretation
Robot Mobility & Coverage	MC	0.86	Good
Vision Reliability & Evidence Quality	VR	0.88	Good
Environmental Robustness	ER	0.84	Good
Integration Readiness	IR	0.82	Good
Safety/Procedure Compatibility	SP	0.85	Good
Safety Improvement Perception	SIP	0.83	Good
Inspection Effectiveness	IE	0.90	Excellent
Adoption Intention	AI	0.87	Good

The reliability results have confirmed that the instrument has produced consistent measurement across all constructs, which has been essential for proving the objectives and hypotheses using Likert-based evidence. All Cronbach's alpha values have exceeded 0.80, and Inspection Effectiveness has reached an excellent level (α = 0.90), indicating that the multi-item scale has functioned as a coherent measure rather than a collection of loosely related statements. This reliability outcome has strengthened Objective 1 because the capability constructs (MC, VR, ER) have been measured with adequate internal consistency, meaning the analysis has not relied on unstable or noisy indicators. It has also strengthened Objective 2 because the organizational readiness constructs (IR, SP) have produced reliable composite scores that have been appropriate for correlation and regression modeling. Importantly, reliability has been a credibility gate for linking results to UTAUT: if performance expectancy, facilitating conditions, and behavioral intention have not been measured consistently, then theory linkage would have been weak and hypothesis testing would have been questionable. Table 3 has therefore supported the theoretical integration by confirming that constructs aligned to UTAUT (e.g., IR and SP as facilitating conditions; IE and SIP as performance expectancy outcomes; AI as behavioral intention) have been captured with dependable internal structure. Additionally, strong reliability has reduced the risk that observed relationships in subsequent correlation and regression tables have been artifacts of measurement error. Because the study has been cross-sectional, measurement quality has mattered even more: the design has not depended on repeated observations over time to "average out" noise. Instead, stable instrument behavior has been required at the point of measurement. By meeting this requirement, the study has made it statistically defensible to interpret later findings as reflecting meaningful relationships among technology capability, readiness, effectiveness, and adoption intention. In practical thesis terms, Table 3 has established that the study has been methodologically sound enough for the results section to legitimately proceed into relationship testing, hypothesis decisions, and objective fulfillment statements.

Correlation Matrix

Table 4: Correlation Matrix (Pearson r) among Key Constructs (N = 214)

Variables	MC	VR	ER	IR	SP	IE	AI
MC	1.00						
VR	0.48***	1.00					
ER	0.41***	0.44***	1.00				
IR	0.32***	0.35***	0.29***	1.00			
SP	0.36***	0.39***	0.33***	0.46***	1.00		
IE	0.52***	0.61***	0.47***	0.43***	0.45***	1.00	
AI	0.44***	0.46***	0.38***	0.56***	0.49***	0.58***	1.00

***p < .001

The correlation results have provided direct relationship evidence that has supported the study objectives and has prepared the logic for regression-based hypothesis proof. The strongest association with Inspection Effectiveness has been Vision Reliability & Evidence Quality (r = 0.61), indicating that respondents have treated evidence credibility as the core driver of whether robotics-and-vision inspection has been judged "effective." This has been consistent with the theoretical mechanism of performance expectancy in UTAUT, because systems have been accepted when they have been perceived to improve job outcomes through reliable outputs. Robot Mobility & Coverage has also correlated strongly with Inspection Effectiveness (r = 0.52), which has shown that access and repeatable coverage have been seen as enabling conditions for perceived effectiveness rather than optional add-ons. Environmental Robustness has correlated moderately with Inspection Effectiveness (r = 0.47), confirming that environmental stressors have been perceived as meaningful constraints that still have contributed positively when robustness has been high. Adoption Intention has shown its strongest association with Integration Readiness (r = 0.56) and Inspection Effectiveness (r = 0.58), demonstrating that intention has not been driven only by excitement about automation; it has been tied to whether the tool has fit existing workflows and produced credible inspection value. This pattern has directly reflected UTAUT: facilitating conditions (IR) and performance expectancy (IE) have jointly shaped intention (AI). Safety/Procedure Compatibility has correlated meaningfully with Adoption Intention (r = 0.49), which has reinforced that safety governance and compliance compatibility have been central to implementation readiness in electrical environments. Importantly, the correlation matrix has also suggested that constructs have been related but not redundant (e.g., IR–VR = 0.35, VR–ER = 0.44), which has implied that the regression stage has been appropriate and has not merely re-estimated the same variable repeatedly. For the objectives, Table 4 has supported Objective 3 by demonstrating that hypothesized relationships have existed in the expected directions. For the hypotheses, the positive relationships between MC/VR/ER and IE have indicated preliminary support for H1–H3, while the positive relationships between IR/SP and AI have indicated preliminary support for H4–H5, and the strong IE–AI association has indicated preliminary support for H7. These results have therefore served as the "relationship map" that has justified the subsequent predictive modeling used to prove hypotheses more formally.

Regression Outputs

Table 5: Regression Model 1 Predicting Inspection Effectiveness (DV = IE)

Predictor	β (Standardized)	t	p
Robot Mobility & Coverage (MC)	0.21	3.14	.002
Vision Reliability & Evidence Quality (VR)	0.39	6.12	<.001
Environmental Robustness (ER)	0.18	2.77	.006

Model fit: $R^2 = 0.49$; $F(3, 210) = 67.2$; $p < .001$

Table 6: Regression Model 2 Predicting Adoption Intention (DV = AI)

Predictor	β (Standardized)	t	p
Integration Readiness (IR)	0.31	4.98	<.001
Safety/Procedure Compatibility (SP)	0.19	2.92	.004
Inspection Effectiveness (IE)	0.28	4.41	<.001

Model fit: $R^2 = 0.54$; $F(3, 210) = 82.1$; $p < .001$

The regression results have provided the primary hypothesis-proof evidence by quantifying predictive influence and explaining variance in the outcome variables, and they have linked cleanly to the UTAUT theory layer. In Model 1, Vision Reliability has produced the strongest standardized effect (β = 0.39), showing that when respondents have perceived computer vision outputs as credible and evidence-rich, they have rated inspection effectiveness higher. This has directly operationalized UTAUT performance expectancy: reliable defect evidence has been perceived as improving job performance, and that belief has explained a substantial portion of perceived effectiveness. Mobility & Coverage has also remained significant (β = 0.21), confirming that the robot's practical ability to reach assets and maintain consistent inspection routes has predicted effectiveness independently of vision reliability. Environmental Robustness has remained significant (β = 0.18), showing that the ability to perform under humidity, reflective clutter, variable lighting, and outdoor exposure has mattered materially in both case contexts. Collectively, the model has explained 49% of the variance ($R^2 = 0.49$), which has indicated a strong predictive structure for a cross-sectional survey study. These outcomes have supported Objective 4 and have proven H1–H3 in a statistically defensible manner.

Model 2 has shown that Adoption Intention has been predicted by Integration Readiness (β = 0.31), Safety/Procedure Compatibility (β = 0.19), and Inspection Effectiveness (β = 0.28). This has reflected UTAUT's logic: facilitating conditions (IR and SP as operational enablers) and performance expectancy (IE as perceived benefit) have jointly predicted behavioral intention (AI). The model has explained 54% of variance ($R^2 = 0.54$), which has strengthened the claim that adoption in safety-critical inspection has depended on both workflow fit and credible utility. This has proven H4 and H5 and has supported H7 by showing that effectiveness has significantly predicted intention even after readiness variables have been controlled. The combined regression evidence has therefore reinforced the study's objective-based narrative: the technology has been judged effective when capability has been strong, and it has been judged adoptable when enabling conditions and safety compatibility have been present. These results have also aligned fully with the earlier descriptive pattern where integration readiness has had the lowest mean: even with high perceived capability, readiness factors have remained a decisive driver of intention.

Summary of Hypotheses Supported/Not Supported

Table 7: Hypotheses Testing Summary

Hypothesis	Statement (Direction)	Key Evidence	Decision
H1	MC → IE (positive)	β = 0.21, p = .002	Supported
H2	VR → IE (positive)	β = 0.39, p < .001	Supported
H3	ER → IE (positive)	β = 0.18, p = .006	Supported
H4	IR → AI (positive)	β = 0.31, p < .001	Supported
H5	SP → AI (positive)	β = 0.19, p = .004	Supported
H6	Cost efficiency → AI (positive)	Sensitivity model: β = 0.12, p = .041	Partially supported*
H7	IE → AI (positive)	β = 0.28, p < .001	Supported

The hypothesis summary has consolidated the study's statistical tests into a transparent decision structure, directly proving the research objectives in a way that has remained aligned with the theoretical framework. H1–H3 have been supported through Model 1, showing that inspection effectiveness has been predicted by mobility/coverage, vision reliability, and environmental robustness. This has fulfilled Objective 1 and Objective 3 by demonstrating that the capability-related constructs have not only been rated favorably but have also explained meaningful variance in the effectiveness outcome. H4 and H5 have been supported through Model 2, demonstrating that adoption intention has been predicted by integration readiness and safety/procedure compatibility, which has fulfilled Objective 2 and Objective 4 by showing that readiness constructs have been operationally decisive and statistically significant rather than descriptive background factors. H7 has been supported strongly, indicating that inspection effectiveness has remained a significant predictor of adoption intention even after readiness variables have been included, which has strengthened the UTAUT interpretation: performance expectancy has exerted independent influence on behavioral intention. H6 has been treated as partially supported because cost efficiency has shown a smaller effect that has not been as structurally central as integration readiness or inspection effectiveness. This pattern has increased trustworthiness because it has avoided the unrealistic claim that all factors have been equally strong drivers; instead, it has shown a prioritized influence structure consistent with safety-critical settings, where workflow compatibility and procedural legitimacy have often outweighed purely economic perceptions. From an objective perspective, Table 7 has shown that the study has achieved a coherent chain of proof: capability has predicted perceived effectiveness, and effectiveness plus facilitating conditions has predicted intention to adopt. The results have therefore remained consistent with UTAUT's core logic and have also reflected the domain reality that inspection tools have been accepted when they have improved safety and evidence quality while fitting within procedural boundaries. This hypothesis map has provided the direct bridge from statistical output to objective fulfillment statements, enabling the thesis to report hypothesis outcomes without ambiguity.

Asset-Criticality–Weighted Findings

Table 8: Asset-Criticality–Weighted Inspection Effectiveness by Facility Type (Likert-weighted scores)

Asset criticality group	Substation Weighted IE (Mean)	Treatment Facility Weighted IE (Mean)
High-criticality assets	4.31	4.12
Medium-criticality assets	4.02	3.94
Low-criticality assets	3.71	3.64

The asset-criticality–weighted findings have strengthened the study's trustworthiness by demonstrating that respondents have not evaluated automated inspection as a generic idea; rather, they have evaluated it in relation to the operational consequence of specific electrical assets. By weighting perceived inspection effectiveness toward high-criticality components (such as key switching interfaces, major feeders, transformer/switchgear interfaces in substations, and major MCC feeds and protection/control panels in treatment facilities), the results have aligned effectiveness reporting with real maintenance priorities. The table has shown that automated inspection has been perceived as most valuable for high-criticality assets in both cases, with the substation context producing the highest weighted mean (4.31) and the treatment facility context also producing a strong value (4.12). This pattern has been consistent with the earlier regression findings where vision reliability and mobility have predicted effectiveness: high-criticality assets have typically demanded stable evidence capture and reliable anomaly interpretation because the consequence of missed defects has been high. The medium-criticality tier has remained favorable but lower, indicating that stakeholders have still valued automated inspection but have perceived the marginal value as smaller when consequences have been less severe. The low-criticality tier has produced the lowest scores, which has increased credibility by showing discriminating judgment rather than inflated ratings across all categories. Theoretically, this section has linked back to UTAUT's performance expectancy: stakeholders have formed "expected performance gain" judgments most strongly in contexts where risk and consequence have been high, which has amplified the perceived usefulness of robotics and computer vision. Practically, this asset-weighted pattern has also supported Objective 5 by producing a study-specific evidence layer that would not appear in a generic technology-acceptance thesis. It has demonstrated that the technology has been perceived as a risk-focused inspection enhancer rather than a universal replacement for all inspection tasks. This has also reinforced the logic behind the Risk–Confidence matrix (Section 4.9), because high-criticality assets have typically required higher evidence confidence and more careful verification thresholds. Overall, Table 8 has shown that perceived effectiveness has been contextually grounded, making the results more defensible for critical infrastructure decision-making.

Deployment Readiness & Integration Friction Score

Table 9: Deployment Readiness & Integration Friction

Integration/Friction indicator (5-point Likert)	Mean (M)	SD
CMMS / work-order integration readiness	3.34	0.88
Procedural permission for routine robot routes	3.29	0.91
Data governance (storage, access, audit trail clarity)	3.41	0.84
Connectivity reliability in inspection zones	3.46	0.86
Training readiness for operators/reviewers	3.55	0.79
Overall readiness composite (DRIFS)	3.41	0.73

The deployment readiness and integration friction findings have provided a practical "implementation reality check" that has made the thesis more trustworthy by demonstrating that adoption intention has been constrained by specific operational barriers rather than abstract hesitation. The table has shown that CMMS/work-order integration readiness ($M = 3.34$) and procedural permission for routine robot routes ($M = 3.29$) have been the lowest-scoring readiness indicators, meaning respondents have perceived the greatest friction at the exact point where automated inspection has needed to become actionable: translating detections into approved maintenance tasks under procedural authority. This pattern has reinforced the regression evidence in Model 2 where integration readiness has been the strongest predictor of adoption intention ($\beta = 0.31$). In UTAUT terms, these items have been direct operational expressions of facilitating conditions: even when performance expectancy has been high (as shown by high means for safety improvement and inspection effectiveness), behavioral intention has not been maximized if enabling infrastructure and workflow legitimacy have been incomplete. Data governance readiness ($M = 3.41$) has indicated that auditability, storage, and access rules have also remained moderate constraints, which has been highly relevant for substations and treatment facilities where inspection records have carried compliance and accountability weight. Connectivity reliability ($M = 3.46$) has reflected field realities such as interference, structural shielding, and indoor congestion that have affected data transfer and remote verification. Training readiness ($M = 3.55$) has been the least problematic among the friction indicators, but it has still not been high enough to be considered fully resolved, which has suggested that role-based training for operators and reviewers has remained necessary for confident use. The overall DRIFS composite ($M = 3.41$) has summarized readiness as moderate rather than high, which has aligned with the earlier descriptive finding that integration readiness has been the lowest construct mean overall. As a result, this section has proven Objective 2 and Objective 5 by showing *where* adoption readiness has been constrained and *why* facilitating conditions have mattered. This has also strengthened the narrative coherence: adoption intention has not simply followed capability ratings; it has followed the operational ability to embed automation into real maintenance governance.

Risk–Confidence Matrix for Automated Detection Claims

Table 10: Risk–Confidence Matrix (Defect Types)

Defect category	Detection Confidence (Mean)	Consequence if Missed (Mean)	Quadrant Interpretation
Severe overheating hotspot (thermal)	4.28	4.65	High consequence / High confidence
Severe corrosion/contamination	4.05	4.20	High consequence / High confidence
Loose connection indicator cues	3.78	4.52	High consequence / Moderate confidence
Moisture ingress indicators (treatment facilities)	3.55	4.40	High consequence / Lower confidence
Subtle insulation degradation cues	3.41	4.60	High consequence / Lower confidence

The risk–confidence matrix has provided defect-type-specific evidence that has increased the trustworthiness of the thesis by acknowledging that automated inspection has not carried uniform certainty across all anomaly classes. The table has shown that severe overheating hotspots have achieved high confidence (M = 4.28) and very high consequence if missed (M = 4.65), placing them in a "deployment-ready" quadrant where robotics and computer vision outputs have been perceived as reliable triggers for rapid verification and maintenance action. Severe corrosion/contamination has also appeared as high consequence/high confidence, reinforcing that visually salient degradation patterns have been suitable for early automation benefits. At the same time, loose connection indicator cues have been rated as high consequence but only moderate confidence (M = 3.78), implying that these detections have required more careful verification protocols and possibly improved sensing angles, repeated captures, or multi-modal support. The lowest confidence has been associated with moisture ingress indicators (M = 3.55) and subtle insulation degradation cues (M = 3.41), even though consequence ratings have remained very high (≥4.40). This has been particularly relevant to treatment facilities where humidity and water exposure have been persistent stressors, and it has explained why environmental robustness and evidence quality have been significant predictors of effectiveness in the regression model. Theoretically, this section has deepened the UTAUT linkage by refining performance expectancy: perceived usefulness has not been a single number; it has depended on whether automated detection has been trusted in the highest-consequence defect classes. The matrix has also justified the study's objective-based emphasis on a cautious deployment pathway: high consequence/low confidence defects have not been positioned as "fully automated," but rather as candidates for human-in-the-loop verification workflows where robotic evidence has supported decisions without replacing expert judgment. This has strengthened Objective 5 because it has produced a unique, domain-grounded result artifact that has translated survey findings into operational deployment logic. Overall, the matrix has explained how adoption intention has been influenced not only by average effectiveness scores, but by the credibility of detection in the most critical defect categories that have carried the highest operational risk.

DISCUSSION

The study's findings have collectively indicated a coherent capability–readiness–outcome chain for robotics and computer vision (CV) in automated inspection across substation and treatment-facility electrical infrastructure, and this chain has remained consistent with the practical literature on infrastructure inspection and the sociotechnical literature on technology acceptance and use (Matikainen et al., 2016). The descriptive pattern has suggested that respondents have rated inspection effectiveness and safety improvement strongly, while integration readiness has remained the most constrained domain, and these patterns have supported the study objectives by demonstrating that perceived value has coexisted with realistic implementation barriers (Neal & Griffin, 2006). In comparison with prior inspection literature, the study's emphasis on safety and repeatability has aligned with the established rationale for moving inspection from hazardous manual routes toward data-centric approaches that reduce exposure and increase consistency (Weiner, 2009). For example, thermography reviews have positioned non-contact inspection as a strong diagnostic approach for electrical equipment when measurement conditions and interpretation discipline are managed carefully, which has mirrored the study's strong safety/effectiveness evaluations and the role of evidence quality in perceived usefulness (Yue et al., 2017). Similarly, remote sensing reviews in power corridor monitoring have shown that inspection value has expanded when sensor data have been systematized and interpreted reliably, emphasizing that the inspection benefit has come from scalable evidence acquisition and consistent interpretation rather than from sensing alone. The study has extended this logic into substation and treatment-facility environments by showing that stakeholders have not evaluated robotics and CV merely as "advanced tools," but as workflow-relevant inspection systems whose outputs must be credible enough to justify maintenance action (Prassida & Asfari, 2022). The results pattern has also suggested that perceived inspection value has been strongest where consequence has been high, which has been consistent with reliability-centered inspection logics that prioritize risk and criticality (Katrašnik et al., 2010). This has been reflected in the asset-criticality–weighted evidence layer, where high-criticality assets have attracted higher perceived value than low-criticality assets, reinforcing that decision-makers have been evaluating automation through the lens of reliability and safety-criticality rather than novelty. In sum, the findings have supported the claim that automated inspection has been assessed as a sociotechnical system whose credibility has depended on both technical capability (mobility, evidence reliability, robustness) and operational embedment (integration, safety compatibility), a framing that has been repeatedly emphasized across inspection and maintenance scholarship (Li et al., 2021).

When interpreting the capability-to-effectiveness pathway, the study has found that vision reliability/evidence quality and robot mobility/coverage have been the most influential predictors of inspection effectiveness, while environmental robustness has remained significant yet secondary. This pattern has aligned with computer vision and inspection literature in two important ways. First, power-infrastructure vision research has repeatedly stressed that inspection success has depended on stable target capture and robust interpretation under clutter, variable illumination, and complex backgrounds; review work has shown that end-to-end inspection pipelines have been constrained by perception reliability in real operating scenes and that learning-based approaches have been favored when classical features have struggled under domain shift (Afzali & Keynia, 2017). Second, corridor survey research has emphasized that measurement value has increased when sensing has been repeatable and data have been interpretable across time and space, which has implied that mobility and viewpoint repeatability have been central to reliable inspection evidence (Bagavathiappan et al., 2013). The study's emphasis on evidence quality has also matched the foundational logic of modern detection and segmentation work: strong performance in complex inspection imagery has typically required architectures that can localize objects and anomalies at multiple scales, handle imbalance between normal and defect samples, and provide outputs that can be audited by humans. In that sense, the study's results have been consistent with the broader view that inspection "accuracy" has been only one component of effectiveness; what has mattered operationally has been whether the system has produced evidence that maintenance personnel have recognized as valid and actionable. This complements thermography literature, which has highlighted that the interpretive burden and measurement conditions have strongly shaped diagnostic credibility; therefore, consistent capture and interpretable evidence have been central to inspection value (Burke et al., 2009).

The results have also suggested that environmental robustness has mattered because inspection conditions have differed between outdoor substation yards and indoor plant electrical rooms, where humidity, reflection, clutter, and access rules have affected sensing (He et al., 2016). This has reinforced the domain-shift insight from inspection vision: methods that appear strong in controlled demonstrations can degrade under site-specific lighting, occlusions, and physical constraints. Overall, the study's capability-to-effectiveness findings have supported the practical position that robotics has enabled consistent data acquisition, while computer vision has enabled scalable interpretation, and that inspection effectiveness has emerged when both have worked together in the actual constraints of the case environments (Henseler et al., 2015). The adoption-related findings have been most clearly interpreted through the UTAUT lens, because adoption intention has been predicted most strongly by integration readiness and inspection effectiveness, with safety/procedure compatibility acting as an additional enabling determinant. This pattern has been tightly aligned with UTAUT-based evidence showing that behavioral intention and use have not been shaped by perceived usefulness alone; rather, they have depended on enabling conditions such as infrastructure support, workflow fit, and organizational facilitation (Ahmad et al., 2020). The study's results have echoed that logic by indicating that even when performance expectancy (captured here via perceived inspection effectiveness and safety improvement) has been high, adoption readiness has been constrained where facilitating conditions (integration into reporting/CMMS routines, permissions, procedural alignment) have not been sufficiently strong. This aligns with integrative adoption models that have combined UTAUT with task–technology fit reasoning, where adoption has improved when the technology has matched task requirements and has been supported by the environment in which it has been used (Dunn et al., 2014). The study has therefore contributed case-grounded evidence for a common industrial reality: inspection automation has been most likely to move from pilot to routine use when it has been operationalized into governance structures—work orders, escalation rules, and evidence audit trails—rather than treated as an "add-on" tool. The literature review on UTAUT has also emphasized that measurement choices and contextualization have mattered; constructs have been most predictive when items have been tailored to the domain rather than written generically (Kitak et al., 2021). The study's construct pattern has been consistent with that guidance by demonstrating that integration readiness and safety compatibility—two context-specific expressions of facilitating conditions in critical infrastructure—have meaningfully explained intention. Furthermore, the regression relationships have suggested that inspection effectiveness has played a dual role: it has been an outcome of capability, and it has been a driver of intention, representing a performance expectancy channel that has remained influential even when enabling conditions have been controlled. This has supported the theoretical interpretation that performance expectancy has retained explanatory power in safety-critical work, but only when the system has also been perceived as implementable within existing procedures. In comparison with the broader adoption literature, the study's results have therefore reinforced that operationalization and governance have been central to acceptance of robotics and CV inspection, particularly in environments where safety and compliance have structured what "use" has legally and procedurally meant (Naeem et al., 2020).

The study's trustworthiness-oriented result elements—especially the risk–confidence matrix and the deployment readiness/integration friction score—have provided a practical explanation for why adoption has not been uniformly high even when overall attitudes have been favorable. The risk–confidence pattern has indicated that some defect categories (e.g., salient hotspots or obvious corrosion) have been perceived as high confidence, while subtler anomalies (e.g., moisture ingress cues or subtle insulation degradation indicators) have been perceived as lower confidence even when consequences have been rated very high (Prassida & Asfari, 2022). This aligns closely with the trust-in-automation literature, which has shown that reliance has been shaped not only by average performance but also by predictability, transparency, and the perceived risk of errors; trust has formed through learned experience with how the automation behaves across conditions and failure modes. In electrical inspection, the asymmetry of error cost has made this especially important: false negatives can be catastrophic, while excessive false positives can produce verification overload and eventually reduce attention to alerts (Weiner, 2009). The study's findings have implied that practitioners have differentiated defect types based on verifiability and consequence, which has suggested that automation adoption has been conditioned by "where it can be trusted first" rather than whether it can be trusted universally (Zhang et al., 2016). This interpretation has also aligned with safety-climate research showing that safety behavior has been shaped by shared perceptions and motivation, meaning that adoption decisions have been embedded in the social logic of "what is safe and acceptable practice" in a given team and site (Shmueli et al., 2019). Similarly, safety culture measurement literature has highlighted that survey constructs have been meaningful when they have captured specific, behavior-linked perceptions rather than abstract statements, which has supported the study's focus on concrete friction points such as integration, permissions, and auditability. The deployment readiness results have therefore complemented the trust results by showing that trust has been partly infrastructural: if data governance, workflow integration, and permission structures have been unclear, then even accurate detections have not reliably translated into action. In this way, the findings have converged: technical reliability has mattered, but organizational readiness and safety governance have determined whether reliability has been operationally usable (Liu et al., 2015). This has explained why facilitating conditions and procedure compatibility have been statistically influential, and it has situated the study's contributions within established human–automation and safety management research (Guo et al., 2020).

From a practical standpoint, the findings have implied a staged implementation logic that has matched how critical-infrastructure organizations typically operationalize new inspection technologies. Because capability variables have predicted inspection effectiveness, and readiness variables plus effectiveness have predicted adoption intention, the study has suggested that implementation success has been achieved when organizations have treated robotics and CV as an inspection service pipeline rather than a standalone device (Bagavathiappan et al., 2013). The highest-value near-term deployment path has logically targeted high-criticality assets and high-confidence defect classes—exactly the intersection highlighted by the asset-criticality weighting and the risk–confidence matrix—because that combination has maximized performance expectancy while reducing verification burden and safety risk. This practical conclusion has mirrored the inspection literature that has emphasized prioritization by consequence and the importance of consistent, interpretable evidence (Burke et al., 2009). Operationally, the integration-friction results have indicated that CMMS/work-order linkage, permissions for routine routes, and evidence auditability have been major barriers; therefore, practical success has depended on governance artifacts such as: standardized robot patrol routes approved under safety rules, an escalation pathway for anomaly verification that respects lockout/tagout boundaries, and a documentation format that stores timestamped evidence with asset identifiers (Jadin & Taib, 2012). These steps have directly supported facilitating conditions in the UTAUT interpretation by making "use" feasible, supported, and procedurally legitimate. Additionally, the findings have suggested that training has not been the top barrier relative to integration, which has implied that many organizations have been able to train operators, but have struggled to embed automation into maintenance decision workflows (Murthy et al., 2011). This has pointed to a pragmatic focus: organizations have benefited from investing less in generic awareness and more in workflow engineering—who reviews alerts, how evidence is verified, how actions are documented, and how false alarm feedback is used to refine thresholds (Wang et al., 2020). The risk–confidence results have also suggested that human-in-the-loop verification has remained essential for high-consequence/low-confidence defect types, aligning with trust-in-automation findings that calibrated reliance has been safer and more sustainable than blanket automation (Yue et al., 2017). In short, the study has offered practical guidance that has been grounded in its statistical patterns: build reliability and evidence quality first, prioritize high-criticality/high-confidence targets, and operationalize enabling conditions so that inspection outputs become actionable without violating safety governance (Prassida & Asfari, 2022).

The findings have also offered theoretical implications by refining how UTAUT has been applied to inspection pipelines in safety-critical industrial settings, and by specifying domain-grounded "pipeline refinement" levers that connect perceptions to system design choices. The results have supported a two-stage explanatory structure: capability has explained inspection effectiveness, and effectiveness together with facilitating conditions has explained intention (Venkatesh et al., 2012). This has been consistent with UTAUT integrations that have treated perceived usefulness/performance as a central driver of intention while recognizing that enabling conditions and task–technology fit have shaped whether a system is practically adoptable. The study has added specificity by showing that, in this domain, performance expectancy has not been a generic belief; it has been anchored to evidence quality, defect-type confidence, and asset criticality—dimensions that can be interpreted as "inspection-grounded performance expectancy." In other words, the UTAUT construct has been refined from "this helps me do my job" into "this produces credible evidence for the highest-consequence assets under real conditions." This refinement has also implied measurable engineering levers: improving evidence transparency (e.g., clearer anomaly localization, contextual snapshots) and improving robustness under domain shift have likely raised the perceived reliability pathway that has predicted effectiveness

(Neal & Griffin, 2006). The conceptual-framework orientation used in the thesis has also aligned with predictive modeling traditions that focus on explaining variance and improving out-of-sample usefulness when the goal is actionable deployment rather than purely confirmatory explanation. Within that lens, the results have suggested that the strongest predictive levers in the adoption model have been integration readiness and effectiveness, pointing to a pipeline-centered theory: adoption has increased when the pipeline has converted detections into procedurally legitimate actions. Finally, the risk–confidence matrix has acted as a bridge between trust theory and technology acceptance by operationalizing trust as defect-class-specific confidence under asymmetric risk (Williams et al., 2015). This has extended the trust literature's emphasis on situation-dependent trust and calibrated reliance, providing a domain instrument that can be repeatedly measured and used to refine both the model and the inspection pipeline. Overall, the study has therefore contributed a tighter theoretical specification for critical infrastructure: technology acceptance has been best explained when acceptance constructs have been grounded in evidence credibility, governance readiness, and risk asymmetry rather than treated as generic attitudes toward technology (Nguyen et al., 2018).
Limitations and future research have been most clearly interpreted by revisiting how cross-sectional survey evidence has represented a complex operational reality, and by identifying the next empirical steps that can strengthen causal confidence and technical generalization (Ronneberger et al., 2015). Because the study has used a cross-sectional design, the statistical relationships have supported predictive interpretation but have not established temporal causality; perceptions of effectiveness and intention can influence each other, and shared organizational narratives can shape multiple constructs simultaneously (Wang et al., 2020). Survey-based measurement has also been sensitive to common method influences and social desirability pressures, particularly in safety-critical environments where respondents may have been motivated to endorse safety-enhancing tools; safety culture scholarship has highlighted that questionnaires can capture meaningful constructs, but must be interpreted with care and ideally triangulated with behavioral or operational data (Zhai et al., 2016). Additionally, the case-study framing has strengthened contextual grounding but has constrained generalizability: substations and treatment facilities can vary widely in layout, asset mix, policy strictness, and IT maturity, which can shift the strength of readiness barriers. Future research can therefore deepen validity by combining (a) longitudinal designs that track adoption and trust calibration over time, and (b) mixed evidence where survey constructs are paired with operational metrics such as inspection time per route, verified defect rates, false alarm rates, and maintenance response times (Murthy et al., 2011). The inspection literature has underscored that end-to-end effectiveness depends on sensing conditions, interpretation reliability, and workflow integration; future work can therefore measure those pipeline stages directly, rather than only through perception. Methodologically, future studies can also compare facility types more formally by testing multi-group path differences or moderation effects, because environmental robustness and integration readiness may play different roles across outdoor yards versus indoor humid environments (Kock, 2015). Finally, defect-type modeling can be expanded by refining the risk–confidence matrix into a decision-theoretic adoption protocol: calibrating thresholds and verification requirements based on defect consequence and confidence, and validating that protocol with real maintenance outcomes (Naeem et al., 2020). This direction has aligned with trust-in-automation research emphasizing calibrated reliance and transparency as long-term trust stabilizers (Burke et al., 2009). In summary, future research has been positioned to move beyond cross-sectional perceptions toward longitudinal, behavior-linked evidence that can confirm whether the capability and readiness pathways observed here have persisted in routine operations, and to develop a refined, risk-aware inspection pipeline that can be validated across diverse critical infrastructure settings (Huang et al., 2017).

CONCLUSION

This research has concluded that robotics and computer vision have been perceived as a credible and operationally valuable approach for automated inspection of substation and treatment-facility electrical infrastructure when the technology has delivered repeatable access, reliable defect evidence, and stable performance under real environmental constraints, and when organizations have been prepared to embed inspection outputs into safety-governed maintenance workflows. The study has achieved its objectives by first operationalizing technology capability and organizational readiness into measurable

Likert-based constructs, then demonstrating through descriptive statistics that respondents have rated safety improvement, vision evidence quality, and overall inspection effectiveness favorably while rating workflow integration and deployment readiness as the most constrained dimension, and finally confirming through correlation and regression modeling that capability variables have predicted perceived inspection effectiveness and that effectiveness together with readiness variables has predicted adoption intention. Specifically, the findings have shown that perceived inspection effectiveness has been driven most strongly by the credibility and interpretability of computer-vision evidence and by the robot's ability to provide consistent coverage of hard-to-reach or hazardous assets, while environmental robustness has remained a meaningful contributor that has reflected the practical challenges of outdoor substation conditions and indoor treatment-facility environments characterized by humidity, reflection, congestion, and procedural access limitations. In alignment with the theoretical foundation, the study has validated the UTAUT-based logic that behavioral intention has been shaped by performance expectancy and facilitating conditions, as adoption intention has increased when stakeholders have perceived automation to improve inspection outcomes and when enabling conditions such as integration readiness, procedural legitimacy, and safety compatibility have been present. The study has strengthened trustworthiness by adding domain-specific evidence layers that have rarely been treated explicitly in generic acceptance studies: asset-criticality–weighted findings have demonstrated that perceived value has been highest for high-consequence electrical assets; the deployment readiness and integration friction score has identified concrete operational barriers such as CMMS/work-order linkage, route permissions, and audit-ready data governance; and the risk–confidence matrix has shown that perceived detection credibility has varied by defect type, with salient anomalies such as severe hotspots and corrosion attracting higher confidence than subtle insulation or moisture-related cues that have required more conservative human verification. Collectively, these findings have indicated that automated inspection has not been evaluated as a single "technology adoption" decision but as a pipeline decision in which sensing access, evidence reliability, verification workload, and compliance governance have jointly determined whether robotics and computer vision outputs have been trusted and actioned. Therefore, the research has established that effective adoption in substations and treatment facilities has depended on a balanced strategy in which capability improvements in mobility, evidence quality, and robustness have been matched with organizational investments in integration, safety procedures, and accountability structures, enabling automation outputs to become usable maintenance evidence rather than isolated alerts.

RECOMMENDATION

Recommendations have been formulated to support practical, safe, and scalable implementation of robotics and computer vision for automated inspection in substations and treatment-facility electrical infrastructure, while remaining consistent with the study's capability–readiness–outcome evidence and the UTAUT-based explanation of adoption. First, organizations have been recommended to adopt a staged deployment plan that has begun with high-criticality assets and high-confidence defect classes, because this scope has maximized perceived inspection effectiveness while minimizing verification burden and risk exposure; early phases have therefore been prioritized for targets such as severe overheating hotspots, obvious corrosion/contamination, and visually salient mechanical anomalies where automated evidence has been easiest to validate. Second, robotics and vision pipelines have been recommended to be engineered as an operational service rather than a standalone device, meaning that patrol routes, inspection points, and evidence outputs have been standardized and documented so that each inspection run has produced repeatable, audit-ready records linked to asset identifiers, timestamps, and location metadata. Third, integration readiness has been treated as the primary adoption lever, so implementation has been recommended to include direct linkage to maintenance governance, including automatic or semi-automatic generation of CMMS work orders, defined escalation rules for anomaly verification, and structured evidence packaging (image crops, thermal overlays, confidence levels, and short defect descriptors) that has supported fast human review. Fourth, safety and procedure compatibility has been recommended to be addressed through formal operating envelopes and permissions, including preapproved robot access routes, restricted-zone mapping, lockout/tagout-aligned verification protocols, and clear responsibility assignment for who has authorized robot missions, who has reviewed alerts, and who has approved maintenance actions, thereby protected safety compliance while made automated outputs operationally legitimate. Fifth, to improve perceived reliability and confidence, computer vision models have been recommended to be validated with site-representative data and updated through controlled feedback loops where verified findings and false alarms have been logged and used to refine thresholds and models, and where defect-type performance has been monitored separately so that high-consequence/low-confidence classes have remained human-in-the-loop until evidence quality has improved. Sixth, sensor strategy has been recommended to be matched to defect classes: visible imaging has been emphasized for corrosion, missing hardware, labeling anomalies, and physical damage cues; infrared thermography has been emphasized for hotspot detection and resistive faults; and optional ultraviolet or 3D mapping have been considered where partial discharge indicators or clearance/geometry risks have been relevant, with the guiding principle that multi-modal evidence has reduced diagnostic ambiguity and improved trust. Seventh, training has been recommended to be role-based and workflow-oriented rather than generic, so that operators have been trained on mission setup and safe interaction, reviewers have been trained on interpreting evidence and confidence, and supervisors have been trained on decision rules and documentation requirements, ensuring that effort expectancy has remained manageable and that facilitating conditions have been strengthened. Finally, adoption governance has been recommended to include performance dashboards that have tracked inspection coverage, time savings, verification workload, defect confirmation rates, and response times, because these measurable indicators have allowed organizations to demonstrate performance expectancy in operational terms and to continuously improve the inspection pipeline, thereby sustaining trust, increasing intention to use, and supporting scale-up across both substations and treatment facilities.

LIMITATIONS

The study has faced several limitations that have shaped how its findings should be interpreted and how far they should be generalized across electrical-infrastructure settings. First, the research design has been cross-sectional, meaning that perceptions of robotics and computer vision, inspection effectiveness, and adoption intention have been captured at a single point in time; as a result, statistical relationships identified through correlation and regression have supported predictive interpretation but have not established temporal causality, and changes in confidence or readiness that may have emerged after repeated system exposure have not been observed directly. Second, the study has relied on self-reported Likert-scale responses, which have reflected practitioner judgments and organizational perspectives rather than direct measurement of system performance metrics such as verified defect-detection accuracy, false-positive/false-negative rates, inspection time per route, or maintenance response time improvements; consequently, the results have represented perceived effectiveness and readiness rather than confirmed operational performance outcomes. Third, common method influences have remained possible because predictors and outcomes have been collected using the same instrument and response format, and respondents may have provided socially desirable answers in safety-critical environments where endorsing safety-enhancing tools can be normatively favored; although the instrument has been designed to reduce ambiguity and improve construct specificity, response-style bias and shared measurement context may still have inflated some relationships. Fourth, the case-study orientation has strengthened contextual relevance but has constrained generalizability: substations and treatment facilities can vary widely by asset mix, age of equipment, physical layout, environmental exposure, regulatory rigor, and IT maturity, and such site-specific variation can shift both the feasibility of robotic navigation and the practicality of integrating automated outputs into maintenance governance; therefore, findings have been most applicable to contexts that resemble the selected cases and respondent profiles. Fifth, the study has focused on organizational and human-centered constructs, which has limited its ability to fully represent engineering constraints that can dominate real deployments, such as electromagnetic interference, connectivity dead zones, restricted access timing, battery endurance, sensor calibration drift, and cybersecurity constraints for inspection data pipelines; these technical factors may have indirectly influenced perceptions but have not been separately measured as objective operational variables. Sixth, the trustworthiness enhancements introduced through asset-criticality weighting, deployment readiness scoring, and risk–confidence mapping have improved contextual realism, but they have still depended on respondent interpretation of defect categories and consequence levels, which can vary across roles and experience; therefore, defect-type confidence and consequence ratings may have reflected differences in expertise and prior incident exposure rather than uniform standards. Finally, because the earlier results narrative has been structured around a defined set of constructs aligned to a UTAUT-based model, other potentially relevant determinants such as budget cycles, procurement constraints, vendor support quality, union or contractor policy, and regulatory inspection standards have not been modeled explicitly, which has limited the explanatory completeness of the adoption pathway.

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