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Electrical Engineering Approaches for AI-Enabled Autonomous Robotics in U.S. Industrial and Defense Applications

Shamsul Arifeen[1];

[1]. DevOps Engineer, Tecsys, Montreal, Canada; Email: shams.feen@gmail.com

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Abstract

This quantitative study examined how electrical engineering approaches influenced the performance of AI-enabled autonomous robotics in U.S. industrial and defense applications. A total of 220 valid responses were analyzed, including 112 industrial (50.9%) and 108 defense (49.1%) system cases, ensuring balanced cross-domain representation. Six electrical engineering constructs were evaluated as predictors of autonomy performance: sensor system performance, embedded computing efficiency, power electronics and energy stability, control and actuation accuracy, communication system reliability, and safety and reliability engineering effectiveness. Descriptive results indicated that safety and reliability engineering demonstrated the highest consistency (M = 4.12, SD = 0.49), followed by control and actuation accuracy (M = 3.94, SD = 0.55) and sensor system performance (M = 3.82, SD = 0.61). Embedded computing efficiency (M = 3.56, SD = 0.74) and power stability (M = 3.41, SD = 0.79) showed the greatest variability across systems. Reliability analysis confirmed strong internal consistency across constructs, with Cronbach's alpha coefficients ranging from 0.842 to 0.926. Multiple regression analysis demonstrated that the combined model significantly predicted autonomy performance ($R^2 = 0.659$, Adjusted $R^2 = 0.647$, $F = 67.83$, $p < .001$). Embedded computing efficiency ($\beta = 0.338$, $p < .001$) and sensor system performance ($\beta = 0.301$, $p < .001$) were the strongest predictors. Power stability ($\beta = 0.256$, $p < .001$) and control accuracy ($\beta = 0.213$, $p < .001$) also significantly contributed. Communication reliability showed a moderate effect ($\beta = 0.158$, $p = .001$) and was stronger in defense contexts, while safety engineering provided a smaller but significant stabilizing influence ($\beta = 0.109$, $p = .014$). Findings confirmed that electrical subsystem performance significantly explained variation in AI-enabled autonomy outcomes across both domains.

Keywords

AI Robotics, Electrical Engineering, Autonomy, Industrial Defense, Performance.

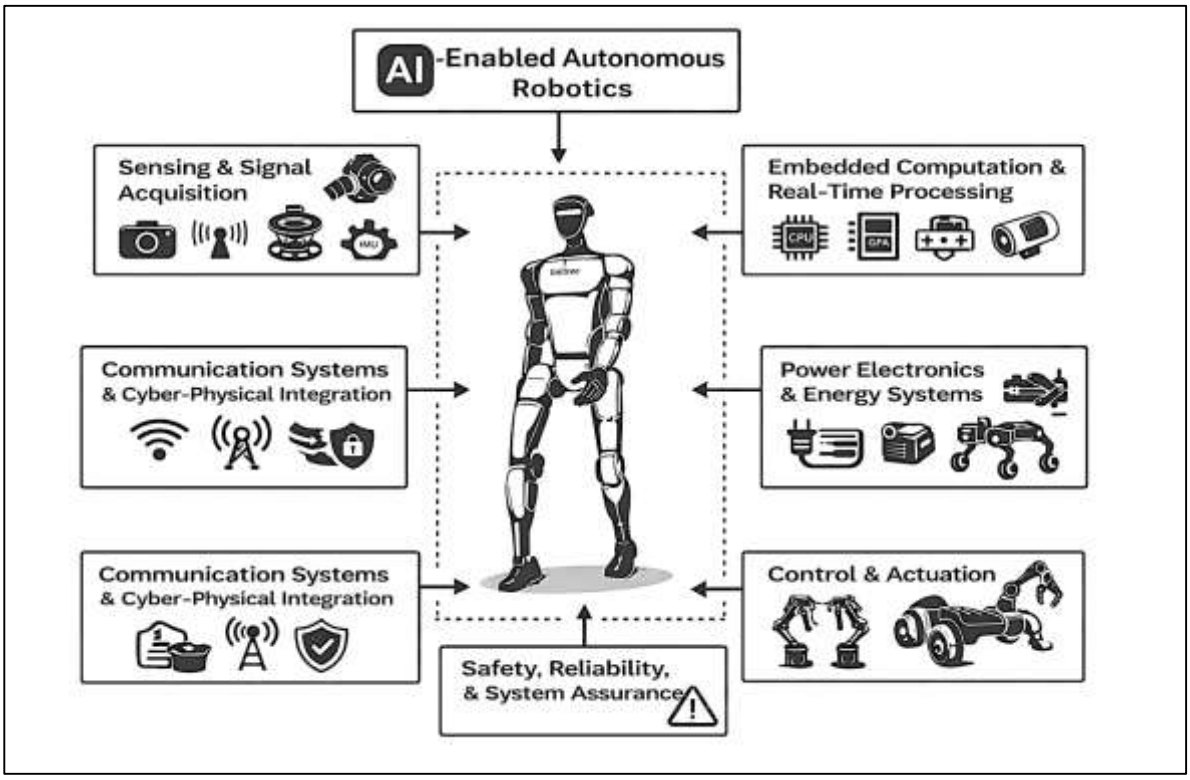
INTRODUCTION

Autonomous robotics can be defined as the design and operation of machines that are capable of sensing their surroundings, interpreting environmental conditions, selecting actions, and executing those actions with minimal direct human control (Bonci et al., 2021). When autonomy is combined with artificial intelligence, the resulting systems are commonly referred to as AI-enabled autonomous robots, meaning that their perception, decision-making, and adaptation capabilities are driven by learning-based computation rather than exclusively rule-based logic. In quantitative research, AI-enabled robotics is treated as a measurable and testable engineering domain because performance can be expressed through numerical metrics such as localization error, control accuracy, task completion time, energy consumption, and system reliability. Electrical engineering approaches form the foundation of this domain because autonomous robots are cyber-physical systems that depend on electrical subsystems for sensing, computing, communications, actuation, and power conversion. These subsystems are not secondary to autonomy; they are structural determinants of whether AI can operate in real-world industrial and defense contexts. At the global level, autonomous robotics has become a strategic technology area because it affects industrial productivity, supply chain resilience, national security modernization, and workforce safety (Chen et al., 2019). Robotics-driven automation influences international manufacturing competitiveness by enabling high-throughput operations with reduced error rates and improved process stability. In defense settings, autonomous systems influence operational capability by extending sensing reach, increasing mission persistence, and enabling complex tasks in hazardous environments. The United States occupies a distinctive position in this field because its industrial base and defense infrastructure represent two of the most demanding autonomy environments: industrial robotics requires high safety assurance and continuous reliability, while defense robotics requires mission robustness under uncertainty and adverse conditions. AI-enabled autonomy in these contexts is not simply a software challenge; it is a system engineering challenge that emerges from electrical architecture, sensor design, real-time computation, electromagnetic compatibility, and energy constraints. As a result, electrical engineering becomes a central discipline for quantifying autonomy performance, since measurable outputs such as sensor fidelity, signal-to-noise ratio, power efficiency, thermal stability, and control-loop timing directly influence AI behavior (Niloy et al., 2021). The intersection of electrical engineering and AI robotics therefore represents a technical pathway for creating autonomous systems that can meet the stringent operational demands of U.S. industrial automation and defense missions while maintaining measurable performance standards suitable for quantitative analysis.

AI-enabled autonomous robotics depends on the integrity and quality of sensory measurement, making sensing and signal acquisition a primary electrical engineering domain. A robot can only behave autonomously if it can measure its own motion and the external environment with sufficient precision, stability, and timeliness (He et al., 2021). Common sensing modalities in industrial and defense robotics include cameras, depth sensors, LiDAR, radar, ultrasonic transducers, inertial measurement units, magnetometers, encoders, and force/torque sensors. Each sensor type produces signals with distinct electrical characteristics, noise behaviors, bandwidth requirements, and calibration needs. The electrical design of sensor interfaces involves analog front-end circuitry, filtering, impedance matching, digitization, and synchronization. These elements directly affect perception accuracy because AI perception models are sensitive to sensor noise, exposure instability, dropped frames, and time misalignment. Quantitative evaluation of autonomy therefore often begins with sensor-level metrics such as measurement variance, drift, bias stability, latency, and sampling jitter. In industrial environments, sensors must remain reliable under conditions such as dust, vibration, reflective surfaces, moving forklifts, dynamic lighting, and electromagnetic interference from machinery. In defense environments, sensors must remain reliable under additional conditions such as smoke, rain, debris, extreme temperatures, and adversarial electronic conditions. These settings make multi-sensor fusion essential, because relying on a single modality produces failure cases that reduce mission reliability. Electrical engineering supports fusion by enabling stable time-stamping, clock discipline, deterministic bus performance, and robust power delivery to sensor arrays. In practice, many autonomy failures in real deployments originate from electrical issues such as connector

looseness, power droop, grounding errors, and timing misalignment rather than algorithmic limitations. Sensor fusion also depends on the physical arrangement of sensors and the stability of calibration parameters (Ezenkwu & Starkey, 2019). The electrical architecture must support consistent sensor triggering, accurate data transport, and sufficient compute throughput for real-time processing. AI perception methods such as object detection, semantic segmentation, and depth inference are constrained by these electrical realities. For example, perception accuracy decreases when sensor bandwidth is limited, when compute throttling reduces inference rate, or when thermal instability causes frame drops. For quantitative robotics research, this means that perception outcomes can be modeled as a function of measurable electrical parameters such as signal integrity, bus throughput, clock stability, and power noise. These relationships become particularly important in U.S. industrial and defense robotics because autonomy systems are expected to function continuously in production environments or during extended missions (Sakai & Nagai, 2022). Therefore, electrical engineering approaches that strengthen sensing reliability provide a measurable pathway for improving autonomy stability and for establishing statistically valid performance comparisons across different robot designs, sensor suites, and application contexts.

Figure 1: AI-Driven Autonomous Robotics Engineering Framework



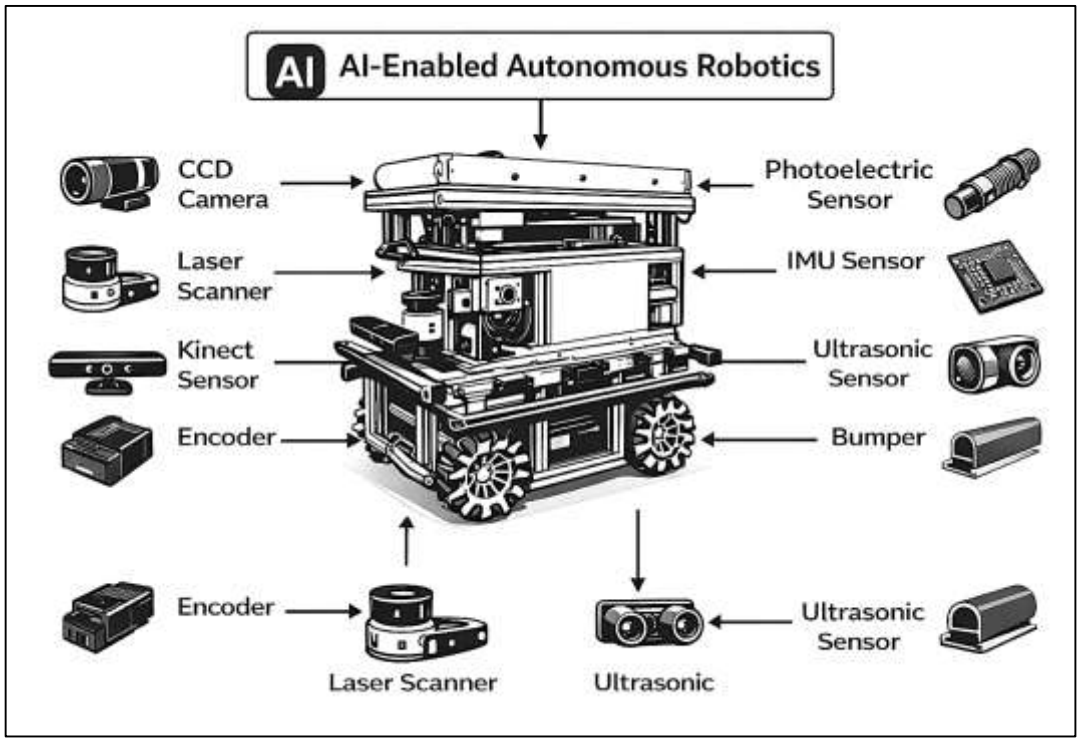
Embedded computation and real-time processing represent a second core electrical engineering dimension of AI-enabled autonomous robotics. Autonomy requires the execution of multiple computational pipelines simultaneously, including perception inference, state estimation, mapping, planning, safety monitoring, and control. These pipelines must operate under real-time constraints because robots interact with physical environments where delays can cause unsafe behavior, collision risk, or task failure (Misaros et al., 2023). The compute architecture therefore becomes a major determinant of autonomy performance. Industrial and defense robots often use heterogeneous computing platforms that include microcontrollers for low-level motor control, CPUs for middleware and scheduling, GPUs for deep learning inference, and specialized accelerators for efficient neural network execution. Electrical engineering determines how these compute units are powered, cooled, synchronized, and integrated into a stable embedded system. Quantitative autonomy performance depends on measurable compute metrics such as inference latency, control-loop timing jitter, memory bandwidth, power consumption, thermal headroom, and fault recovery time. In industrial settings,

robots may need to execute high-frequency control while also performing real-time visual inspection, obstacle detection, and path planning in dynamic workspaces. In defense settings, robots may need to execute these same tasks while also operating under limited power, intermittent connectivity, and high uncertainty. These demands require electrical engineering approaches that prioritize compute efficiency and system reliability. Power delivery design influences whether the compute system can sustain peak load without voltage droop or brownouts (Kostavelis et al., 2019; Rauf, 2018). Thermal design influences whether processors can maintain stable clock rates or will throttle under sustained load. Board-level layout influences electromagnetic emissions and susceptibility, which can affect sensor buses and communication channels. These factors create measurable relationships between electrical design and AI performance. For instance, a deep learning model may demonstrate high accuracy in laboratory testing but become unstable in deployment if compute throughput decreases under thermal constraints (Haque & Arifur, 2021; Zaman et al., 2021). Similarly, a planning algorithm may become unsafe if scheduling delays introduce control lag. Real-time operating systems and deterministic scheduling are often necessary for guaranteeing control timing, and these software approaches depend on electrical-level support such as stable clock sources and robust I/O. Additionally, the choice of embedded compute affects autonomy capability in measurable ways because it defines the maximum achievable inference rate and the complexity of models that can run on-board. Larger models can improve perception accuracy, while smaller models can improve responsiveness and energy efficiency (Hentout et al., 2019; Rashid & Sai Praveen, 2022; Ratul & Subrato, 2022). In quantitative research, these trade-offs can be evaluated through metrics such as task completion success rates, collision avoidance reliability, mean time between failures, and energy cost per mission. The U.S. industrial and defense robotics landscape places strong emphasis on edge autonomy, which requires that AI computation occur locally on the robot rather than relying on remote servers. This local execution requirement elevates electrical engineering approaches to embedded system integration as a central factor in determining whether AI-enabled autonomous robots can achieve robust and repeatable performance under real-world operational constraints.

Power electronics and energy systems are fundamental in autonomous robotics because autonomy is sustained by energy conversion, storage, and distribution across sensing, computing, and actuation. A robot's capability to operate autonomously for extended periods depends on its power budget, energy density, and the efficiency of its electrical subsystems. Industrial robots often operate in facilities where charging and maintenance cycles must align with production schedules, while defense robots must often operate for extended mission durations in environments where recharging infrastructure is limited (Castro et al., 2021). These requirements make power engineering a major factor in autonomy effectiveness. Autonomous robots typically rely on batteries, fuel cells, hybrid systems, or tethered power depending on mission constraints. Electrical engineering approaches include battery management systems, state-of-charge estimation, state-of-health monitoring, DC-DC conversion, inverter design, and regenerative braking strategies. Each of these affects measurable autonomy outcomes such as operational time, speed consistency, payload capability, and thermal stability. In mobile robotics, power constraints influence the selection of sensors and compute platforms because high-performance perception and mapping often require significant energy. A robot may be forced to reduce sensor sampling rates or inference frequency to preserve mission endurance, and these adjustments directly affect autonomy accuracy. Power delivery noise can also affect sensor readings and communication integrity, meaning that stable regulation and filtering are not merely efficiency concerns but perception reliability concerns (Xu et al., 2019). Motor drives represent a major portion of energy use in many robotic systems. Electrical engineering design choices such as motor type selection, current control bandwidth, drive switching frequency, and torque ripple minimization influence motion smoothness and tracking accuracy. In industrial settings, precise actuation is necessary for tasks such as material handling, assembly, and automated inspection. In defense settings, precise actuation is necessary for navigation over uneven terrain, stabilization of payloads, and manipulation tasks under uncertainty. Quantitative evaluation of power systems in autonomy can include metrics such as watt-hours per kilometer, joules per manipulation cycle, thermal rise per mission, and voltage stability under peak actuation loads. Energy-aware planning is also increasingly integrated into autonomy

software, meaning that electrical system models become part of the decision-making process. A robot may select paths based on energy cost or may adjust behavior to prevent battery depletion. These behaviors are measurable and can be analyzed statistically across mission trials. Power system reliability is equally important, as failures in connectors, wiring harnesses, or power electronics can cause mission termination. Industrial robots require high uptime and predictable maintenance intervals, while defense robots require fault tolerance under harsh conditions (Abbass, 2019). Therefore, electrical engineering approaches to power system robustness—including redundancy, fault detection, and protective circuitry—directly support the reliability metrics that define autonomy success. In U.S. industrial and defense applications, where robots are expected to function as mission-critical assets rather than experimental prototypes, the quantitative role of power electronics and energy engineering becomes central to understanding and improving AI-enabled autonomous robotics.

Figure 2: Autonomous Robotics Engineering Sensor Framework



The primary objective of the quantitative study titled Electrical Engineering Approaches for AI-Enabled Autonomous Robotics in U.S. Industrial and Defense Applications is to measure and model how electrical engineering design choices influence the operational performance of AI-enabled autonomous robots across two high-demand U.S. contexts: industrial automation and defense missions. This objective is grounded in the view that autonomy outcomes are not determined by AI algorithms alone, since autonomy emerges from the measurable interaction among sensing integrity, embedded computation stability, real-time control fidelity, communication reliability, and power-system efficiency within a cyber-physical platform. Accordingly, the study aims to quantify the relationships between key electrical engineering variables and autonomy performance indicators under controlled experimental conditions. At the input level, the objective is to evaluate how sensor-interface quality, synchronization accuracy, and signal integrity affect perception-dependent metrics such as object detection consistency, localization drift, and obstacle recognition reliability. At the processing level, the objective is to examine how embedded computer architecture, energy-per-inference behavior, and thermal stability influence latency distributions, inference throughput, and end-to-end response time from perception to actuation. At the power level, the objective is to determine how power conversion efficiency, voltage stability under peak loads, battery management accuracy, and thermal rise impact mission duration, speed consistency, and the rate of autonomy degradation under sustained operation. At the actuation and control level, the objective is to measure how motor drive bandwidth,

feedback sensor resolution, torque ripple behavior, and control-loop jitter affect tracking error, stopping performance, path-following stability, and manipulation precision. At the communication level, the objective is to quantify how network latency, packet loss frequency, timing drift, and electromagnetic susceptibility influence coordination stability, command delivery reliability, and safety-critical responsiveness in distributed robotic architectures. A central objective is also to compare how these electrical engineering factors behave differently across industrial and defense scenarios, since industrial environments emphasize continuous uptime, structured workflows, and proximity safety, while defense environments emphasize ruggedness, mission persistence, and resilience under harsh operational conditions. Overall, the objective is to produce statistically testable evidence on the extent to which specific electrical engineering approaches predict autonomy quality, enabling performance benchmarking based on measurable electrical parameters and supporting rigorous experimental comparisons among alternative robotics system configurations.

LITERATURE REVIEW

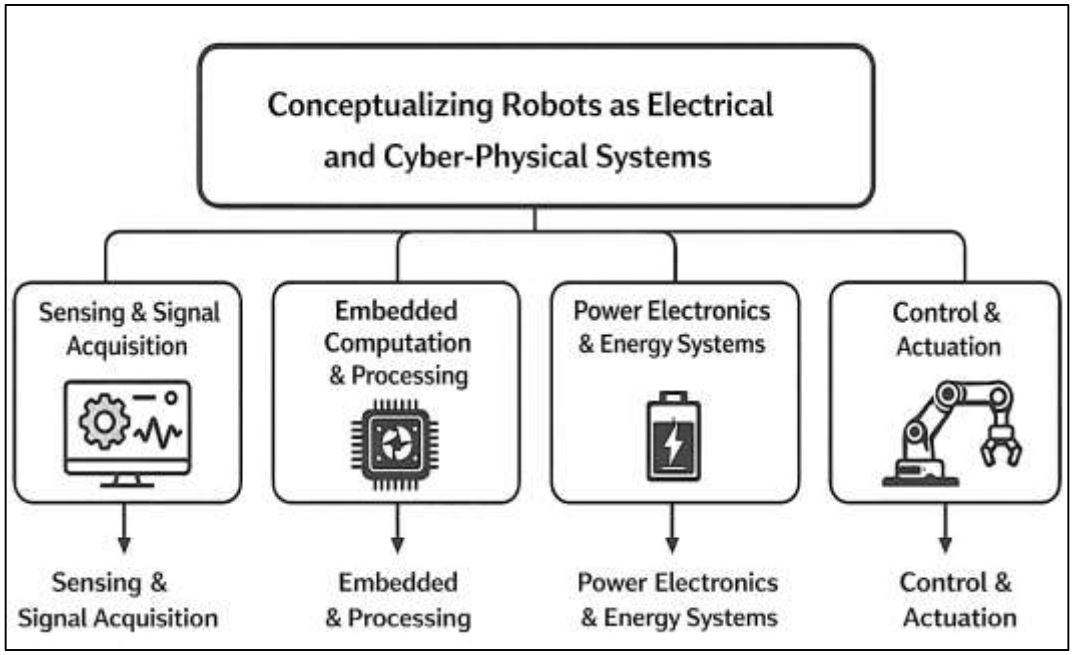
The literature on AI-enabled autonomous robotics spans multiple engineering and computational disciplines, with electrical engineering forming a foundational layer that directly influences autonomy performance, safety, and reliability. Within this body of work, autonomous robotics is consistently treated as a cyber-physical system in which sensing, computation, control, communication, and power subsystems interact to produce measurable behavioral outcomes. The literature review for this study focuses on examining how electrical engineering approaches have been empirically linked to autonomy effectiveness, particularly in applications where operational demands are high and failure tolerance is low (Ferreira & Reis, 2023). U.S. industrial and defense environments represent two such contexts, as they impose strict performance, safety, and reliability requirements that necessitate rigorous electrical system design. Existing studies frequently report quantitative metrics such as localization error, control latency, energy efficiency, system uptime, and fault rates, demonstrating that autonomy quality is closely tied to electrical subsystem characteristics rather than algorithmic design alone. The literature further reveals that AI-driven perception, planning, and control are constrained by sensor fidelity, embedded compute capacity, timing stability, and power availability, making electrical engineering a primary determinant of system-level autonomy outcomes (He et al., 2021). This review synthesizes prior empirical and experimental research by organizing the literature around measurable electrical engineering domains and their reported impacts on autonomous robotic performance. The section is structured to progressively examine sensing and signal acquisition, embedded computation, power electronics, control and actuation, communication systems, safety and reliability engineering, and domain-specific adaptations for industrial and defense applications. By organizing the literature in this manner, the review establishes a quantitative foundation for identifying variable relationships, measurement approaches, and performance benchmarks that inform the present study's analytical framework (Soni & Kaur, 2023).

AI-Enabled Autonomous Robotics

Autonomous robots are widely conceptualized in the literature as complex electrical and cyber-physical systems in which physical processes and computational intelligence are tightly integrated through continuous electrical interaction. Rather than being viewed as purely mechanical machines augmented by software, autonomous robots are framed as electrically mediated systems where sensing, computation, actuation, and communication operate as interdependent layers governed by real-time electrical signals (Faysal & Bhuya, 2023; Pookkuttath et al., 2021; Rifat & Jinnat, 2022). This conceptualization emphasizes that autonomy arises from the closed-loop interaction between physical dynamics and digitally implemented decision-making processes. Electrical subsystems serve as the interface between the robot and its environment, enabling the acquisition of sensor data, the execution of control commands, and the enforcement of timing constraints necessary for stable operation. Within this framing, cyber-physical integration is not abstract but measurable, as electrical signals encode environmental perception, internal state estimation, and control intent(Habibullah & Aditya, 2023; Jahangir & Mohiul, 2023). The literature consistently treats robotic autonomy as an emergent property of this integration rather than as an isolated algorithmic capability. Studies in robotics systems engineering describe how failures in electrical synchronization, power distribution, or signal integrity can directly undermine autonomous behavior, even when high-performing AI algorithms are present

(Huang et al., 2021). This systems-level perspective has been reinforced by empirical research demonstrating that real-world autonomy performance degrades when electrical assumptions made during algorithm design are violated in deployment environments. Consequently, autonomous robots are positioned in the literature as electrically grounded systems whose intelligence is constrained, enabled, and shaped by their electrical architecture. This view is particularly dominant in industrial automation and defense robotics research, where operational reliability, safety assurance, and performance consistency require that electrical and computational components function as a unified system (Singh et al., 2023). The conceptualization of autonomous robots as electrical and cyber-physical systems therefore provides the foundational lens through which autonomy performance is evaluated, measured, and compared across platforms and applications.

Figure 3: Electrical Foundations of Autonomous Robotics Systems



Electrical subsystems are consistently identified in the literature as the primary enablers of AI-driven autonomy, serving as the infrastructure upon which intelligent behavior is executed. Sensor interfaces, embedded processors, power electronics, motor drives, and communication buses collectively determine whether AI algorithms can operate under real-world constraints (Wang et al., 2021). Research in autonomous systems repeatedly shows that perception accuracy, decision latency, and control fidelity are bounded by electrical subsystem performance. Sensor electronics define measurement resolution, noise characteristics, and timing precision, which directly influence the quality of data available for AI inference. Embedded computing hardware determines the complexity of models that can be deployed, the speed at which decisions can be made, and the energy cost associated with continuous operation. Power systems regulate the availability and stability of energy required to sustain computation and actuation, while communication subsystems govern data exchange within distributed architectures. The literature emphasizes that AI-driven autonomy does not function independently of these components, as learning-based models require stable electrical environments to maintain consistent behavior (Caldwell et al., 2020). Experimental studies in both mobile robotics and industrial manipulators document how voltage instability, thermal constraints, or communication delays can cause learned policies to deviate from expected behavior. Electrical subsystems also play a critical role in safety-related functions, including emergency stopping, fault detection, and system isolation. These capabilities are particularly emphasized in industrial and defense robotics research, where autonomous systems operate in proximity to humans or within mission-critical environments. As a result, electrical engineering is not treated as a supporting discipline but as a central determinant of autonomy capability. The literature reflects a consensus that

improvements in AI performance are often limited by electrical system constraints rather than by algorithmic deficiencies (Rashid et al., 2023; Khaled & Mosheur, 2023; Saad et al., 2019). This recognition has led to an increased emphasis on co-design approaches in which electrical engineering decisions are aligned with AI requirements to achieve stable, measurable autonomy outcomes.

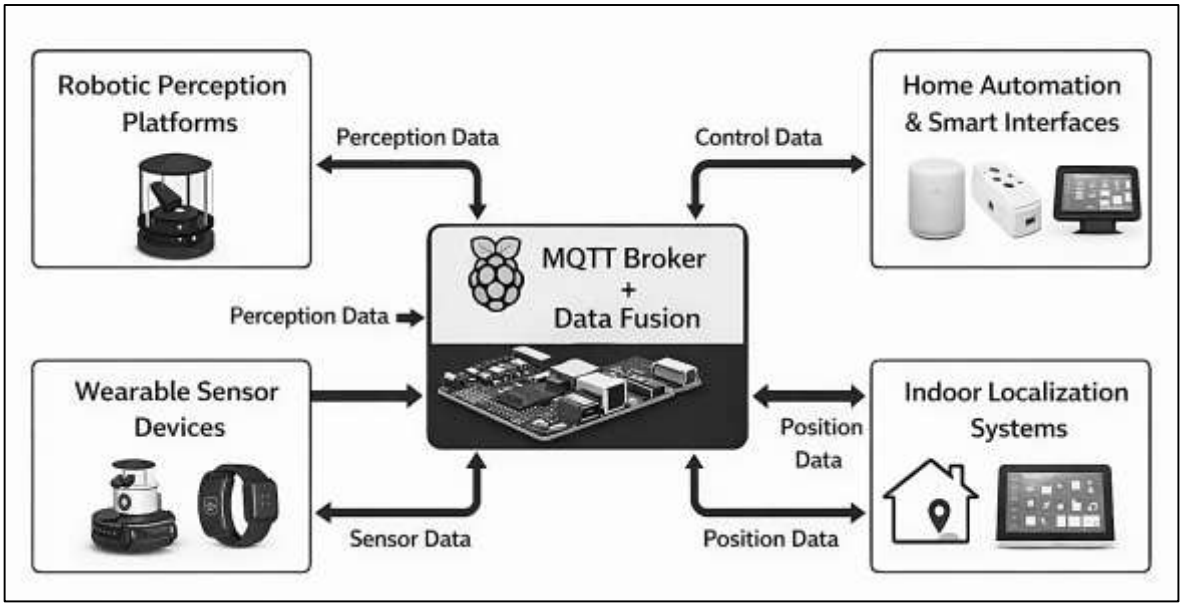
Sensor Systems and Signal Acquisition in Autonomous Robotics

Sensor systems represent the primary interface between an autonomous robot and its operational environment, and the literature consistently positions sensing as the first quantitative determinant of autonomy quality. In AI-enabled autonomous robotics, perception accuracy is fundamentally constrained by the electrical characteristics of sensors and their signal acquisition chains (Li et al., 2021). A central theme in sensing research is the relationship between signal-to-noise ratio and the reliability of perception outputs, since AI perception models depend on stable and high-quality measurements. Sensor noise influences both classical estimation pipelines and learning-based perception systems by increasing uncertainty, producing false detections, and reducing feature stability. This effect is measurable in metrics such as object detection consistency, depth estimation variance, and localization drift. The literature also emphasizes sampling frequency, resolution, and bandwidth limitations as critical electrical parameters that govern whether perception can be executed in real time. High-resolution sensing produces richer information but increases data throughput requirements, which can saturate sensor buses and memory systems (Karalekas et al., 2020; Mostafa, 2023; Rifat & Rebeka, 2023). Conversely, low sampling frequency can reduce temporal continuity, causing missed detections and delayed obstacle recognition in dynamic environments. These relationships are widely documented across studies involving cameras, inertial sensors, LiDAR, radar, and ultrasonic sensors. Electrical noise and drift are also recurrent themes, particularly for inertial measurement units, encoders, and analog force sensors, where bias instability can accumulate over time and distort state estimation. Calibration stability is treated as a measurable property rather than a one-time setup process, since sensor calibration parameters can change due to vibration, thermal shifts, mechanical stress, and aging. The literature demonstrates that sensor calibration quality affects mapping accuracy and task performance, especially in long-duration deployments (Alatise & Hancke, 2020; Md & Sai Praveen, 2024; Sai Praveen, 2024). These sensing limitations are not merely theoretical concerns; they are empirically linked to autonomy outcomes in industrial and defense robotics. As a result, the sensor acquisition chain is frequently treated in robotics literature as a system whose electrical properties must be quantified and controlled in order to support repeatable and statistically valid autonomy performance.

Multi-sensor fusion is widely discussed in the literature as a systems-level response to the limitations of single-sensor autonomy, and electrical engineering perspectives emphasize that fusion performance depends heavily on time alignment, interface behavior, and measurement consistency (Schmidt et al., 2020). Sensor fusion frameworks combine complementary modalities such as cameras, IMUs, LiDAR, radar, and wheel odometry to produce a unified state estimate and environmental representation. Within this fusion process, time synchronization error is treated as a quantitative variable that can significantly influence localization and mapping accuracy (Begum, 2025; Faysal & Aditya, 2025). The literature documents that even small timing misalignments can create measurable errors in pose estimation, because sensor observations are incorrectly associated with robot motion states. Synchronization error is therefore often measured through timing drift distributions, timestamp jitter, and cross-sensor alignment variance. Sensor interface latency is another major factor discussed in the literature, particularly in robotics systems where sensor data must travel through buses, middleware layers, and processing pipelines before being fused. Latency can lead to stale measurements, causing localization drift and unstable tracking when robots move quickly or when the environment changes rapidly. These effects are documented across visual-inertial, LiDAR-inertial, and radar-assisted localization studies. The literature also highlights redundancy and sensor diversity as fault-tolerance strategies, where the presence of multiple sensor modalities allows autonomy to continue under partial sensor failure or degradation (Jahangir, 2025; Xia et al., 2023). Redundant sensing is not only associated with improved accuracy but also with improved reliability and safety, since the autonomy system can detect inconsistencies among sensors and identify abnormal behavior. Sensor diversity is particularly important because different modalities fail under different conditions, such as cameras under low light, LiDAR under heavy rain or dust, and GPS under interference. Fusion approaches therefore emphasize

complementary failure modes. The electrical engineering dimension becomes critical because sensor fusion performance depends on stable synchronization, deterministic data transport, and reliable power delivery to sensor arrays. Studies in robotics systems integration show that fusion quality decreases when bus congestion, packet drops, or timing jitter increases (Ignatious & Khan, 2022). Therefore, the literature supports the position that multi-sensor fusion is not purely an algorithmic solution but an electrical and system integration challenge, where quantitative performance depends on measurable timing, latency, and reliability characteristics of the sensing subsystem.

Figure 4: Sensor Systems for Autonomous Robotics Engineering



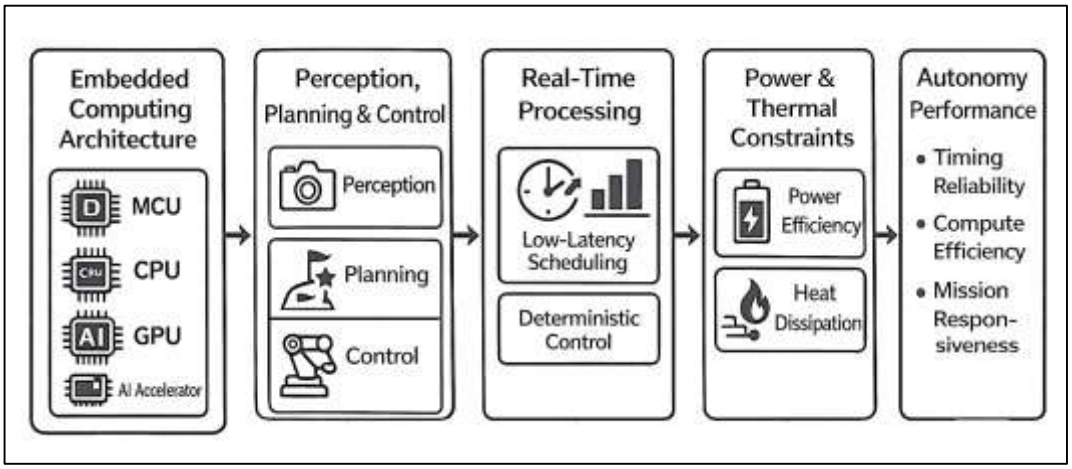
The literature also distinguishes sensor deployment requirements in industrial environments from those in defense environments, emphasizing that sensing must be engineered for context-specific interference conditions. Industrial robotics research highlights those factories, warehouses, and production floors introduce distinct sensing challenges, including reflective surfaces, repetitive textures, moving machinery, dynamic lighting, and electromagnetic noise from motors, welders, conveyors, and industrial control equipment (Yeong et al., 2021). These factors affect camera exposure stability, LiDAR reflectance consistency, and radar clutter, producing measurable variations in perception accuracy. Dust and airborne particles in industrial environments can degrade optical sensors, while vibration from heavy machinery can alter calibration and increase measurement noise in inertial sensors. The literature often describes these effects using quantifiable interference metrics such as vibration amplitude, particulate density, and electromagnetic emission levels. In defense robotics, sensor deployment constraints are often more severe and include extreme temperatures, water exposure, mud, smoke, battlefield debris, and contested electromagnetic conditions. These conditions increase sensor dropout rates, degrade measurement quality, and raise the probability of sensor misclassification in AI-based perception (Cong et al., 2021).

Embedded Computing Architectures for Autonomous Robotics

Embedded computing architectures are widely presented in the literature as the operational backbone of AI-enabled autonomous robotics because they determine whether perception, localization, planning, and control can be executed under real-world constraints. Autonomous robots require a computing stack capable of supporting heterogeneous workloads, including high-rate sensor processing, probabilistic estimation, deep learning inference, optimization-based planning, and real-time control (Syeedur, 2025; Amin, 2025; Mejias et al., 2021). The literature emphasizes that these workloads differ substantially in computational structure and timing requirements, motivating heterogeneous compute platforms that combine microcontrollers, CPUs, GPUs, and AI accelerators within a single robotic system. Microcontrollers are typically described as essential for deterministic low-level tasks such as

motor control, safety monitoring, and sensor polling, where predictable timing is more critical than raw compute power. CPUs are commonly framed as the general-purpose backbone for middleware, system orchestration, and multi-threaded robotics pipelines, supporting tasks such as map management, behavior planning, and network communication. GPUs are widely identified as enabling high-throughput parallel computation, making them particularly effective for deep neural network inference in perception tasks such as object detection, segmentation, and depth estimation. AI accelerators, including tensor processing units and dedicated neural inference engines, are discussed as specialized hardware that improves energy efficiency and throughput for specific model architectures (Md. Towhidul & Rebeka, 2025; Ratul, 2025; Wan et al., 2021). Across these studies, compute throughput and inference latency are consistently treated as measurable dependent variables because they directly influence the speed and responsiveness of autonomy. When inference latency increases, robots experience delayed perception updates, which can increase obstacle avoidance error, reduce tracking accuracy, and destabilize navigation (Rifat, 2025; Azam, 2025). Similarly, when compute throughput is insufficient, robots may reduce sensor frame rates or model complexity, which can degrade perception accuracy and decision quality. The literature also stresses that embedded autonomy performance cannot be predicted solely by theoretical compute capability, because performance depends on memory bandwidth, bus contention, scheduling overhead, and software stack efficiency. Therefore, quantitative robotics studies frequently benchmark compute platforms using end-to-end metrics such as perception pipeline latency, localization update frequency, and control response time (Ingrand, 2019). This body of work positions heterogeneous embedded computing not as a convenience but as a requirement for modern autonomous robotics, particularly in industrial and defense systems where autonomy must remain stable under sustained operation and variable mission conditions.

Figure 5: Embedded Computing for Autonomous Robotics Systems



Real-time processing and scheduling are central themes in the embedded robotics literature because autonomous robots operate in physical environments where timing guarantees directly affect stability and safety (Neuman et al., 2022). The literature distinguishes between autonomy components that can tolerate variable timing and those that require deterministic execution. High-level planning and mapping may tolerate occasional delays, while low-level control and safety monitoring require strict timing constraints. Control-loop timing jitter is repeatedly described as a critical measurable variable, as even small variations in loop timing can cause oscillatory behavior, reduced tracking precision, and unstable actuation in dynamic conditions. Deadline miss rates are also emphasized in studies of real-time robotics, where a missed control deadline can translate into a delayed braking response, a late obstacle avoidance maneuver, or an incorrect stabilization command. These timing behaviors are measurable through latency distributions, scheduling trace analysis, and closed-loop performance degradation under load. The literature frequently contrasts deterministic execution models, which prioritize predictable timing and bounded latency, with best-effort execution models, which maximize throughput but allow variable delays (Tang et al., 2020). Deterministic models are often associated with real-time operating systems, priority scheduling, and time-triggered architectures, while best-effort

models are commonly associated with general-purpose operating systems and non-deterministic middleware. In robotics deployments, the literature reports that deterministic execution is particularly important in safety-critical environments such as industrial automation, where robots operate near humans and equipment. In defense robotics, deterministic execution is similarly important because robots must maintain stability under uncertain terrain and operational stress. However, the literature also notes that AI-enabled perception workloads can introduce unpredictable compute bursts, making real-time scheduling more difficult when perception and control share the same compute resources. As a result, many studies highlight architectural separation as a practical strategy, such as assigning control loops to microcontrollers while assigning perception inference to GPUs or accelerators (Aubin et al., 2022; Tasnim, 2025; Zaheda, 2025b). The literature also identifies communication middleware as a contributor to timing variability, as message passing overhead can increase jitter and introduce unpredictable latency. Therefore, real-time scheduling is treated not only as a software design issue but as a system-level computing architecture problem. Across this research, timing determinism emerges as a measurable enabler of autonomy reliability, linking embedded scheduling decisions to quantitative safety and performance outcomes.

Power Electronics and Energy Management in Autonomous Robots

Power electronics and energy management are consistently treated in the literature as foundational enablers of autonomous robotic operation, because all sensing, computation, communication, and actuation functions ultimately depend on stable and efficient electrical power delivery (Doumbia et al., 2019). Electrical power architecture design in autonomous robots typically centers on the integration of energy storage systems, power conversion stages, and voltage regulation mechanisms that together ensure continuous and reliable operation under dynamic loads. Battery systems are widely discussed as the dominant energy source for mobile autonomous robots, with design considerations extending beyond nominal capacity to include discharge characteristics, internal resistance, thermal behavior, and aging effects. Power converters and voltage regulators are responsible for distributing energy to heterogeneous subsystems that operate at different voltage and current levels, including sensors, processors, communication modules, and motor drives (Singh et al., 2023; Zaheda, 2025a). The literature emphasizes that these conversion stages must maintain regulation accuracy under rapidly changing load conditions, particularly during acceleration, braking, or manipulation tasks that impose peak actuation demands. Power stability under peak loads is repeatedly identified as a critical variable, as voltage sag or transient instability can disrupt sensor timing, reset computing modules, or degrade motor control accuracy. Empirical studies in robotics systems integration document that many autonomy failures originate from power architecture limitations rather than algorithmic deficiencies. For example, sudden current spikes from actuators can introduce electrical noise that propagates through the power distribution network, affecting sensitive sensing and computing components. The literature also highlights the importance of power architecture topology, grounding strategies, and electromagnetic compatibility in maintaining system integrity. Poor grounding or insufficient filtering can increase susceptibility to interference, leading to inconsistent sensor readings or communication errors. As a result, power electronics are framed not only as efficiency components but as system-level reliability enablers. In industrial and defense robotics, where autonomous platforms are expected to operate for extended periods and under variable mechanical stress, power architecture design becomes a measurable determinant of autonomy robustness (Aubin et al., 2022). Studies consistently show that well-designed power systems improve uptime, reduce fault rates, and stabilize overall system behavior, reinforcing the central role of electrical power engineering in autonomous robotic systems.

Energy consumption metrics are widely used in the literature to quantitatively evaluate the operational efficiency and endurance of autonomous robots. Mission duration and energy depletion rates are among the most commonly reported indicators, as they directly reflect how long a robot can sustain autonomous operation before requiring recharging or maintenance (García Núñez et al., 2019). These metrics are influenced by a combination of factors, including propulsion efficiency, sensor duty cycles, computational workload, and environmental conditions. The literature frequently describes energy depletion as a dynamic process rather than a constant rate, since energy use fluctuates based on task intensity, terrain complexity, and interaction frequency. Measures such as energy consumed per task and energy consumed per unit distance traveled provide a normalized basis for comparing autonomy

efficiency across different platforms and operational scenarios. These metrics allow researchers to isolate the energy cost of specific behaviors, such as navigation, manipulation, or perception-intensive inspection. In industrial robotics, energy consumption metrics are often tied to productivity considerations, as robots are expected to operate continuously with minimal downtime. In defense robotics, these metrics are tied to mission persistence and logistical feasibility, since energy replenishment may be limited or unavailable (Mikołajczyk et al., 2023). The literature also highlights that energy consumption is not evenly distributed across subsystems. Actuation typically dominates energy use during motion, while perception and computation dominate during sensing-intensive tasks or idle monitoring. This uneven distribution motivates detailed energy profiling studies that measure subsystem-level consumption and identify opportunities for optimization. Additionally, energy efficiency is often linked to thermal behavior, as higher energy draw leads to increased heat generation, which can affect system reliability. Quantitative studies frequently report trade-offs between energy efficiency and performance, such as increased perception accuracy at the cost of higher power consumption. These trade-offs are treated as measurable design constraints rather than qualitative observations. By grounding autonomy evaluation in energy metrics, the literature provides a framework for statistically comparing robotic systems and understanding how electrical design choices influence operational efficiency across industrial and defense contexts (Sarker et al., 2021).

Figure 6: Power Systems for Autonomous Robotics

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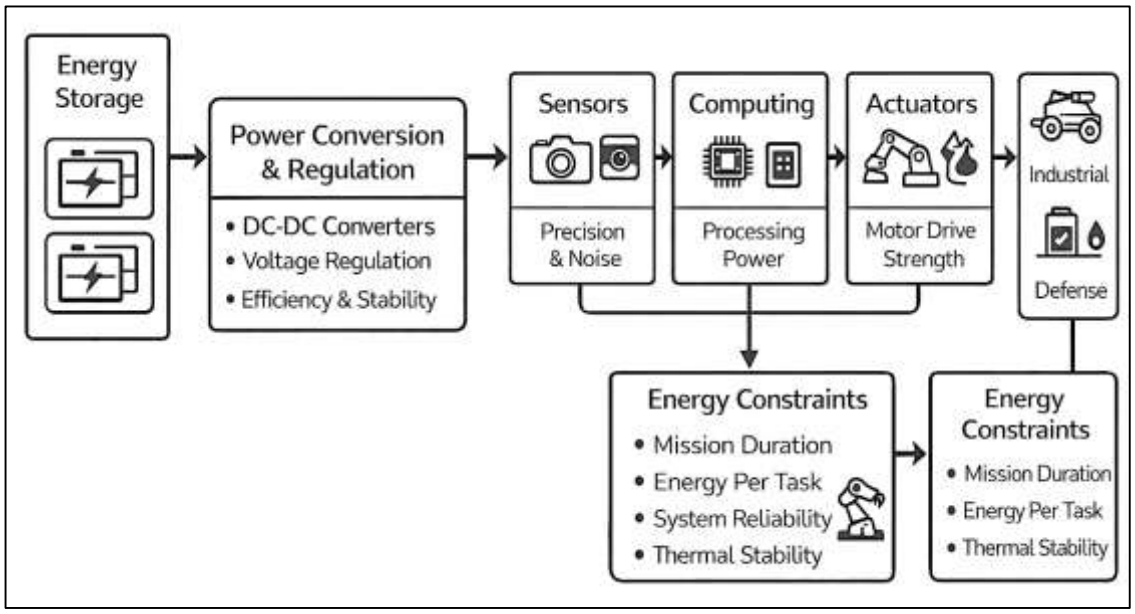
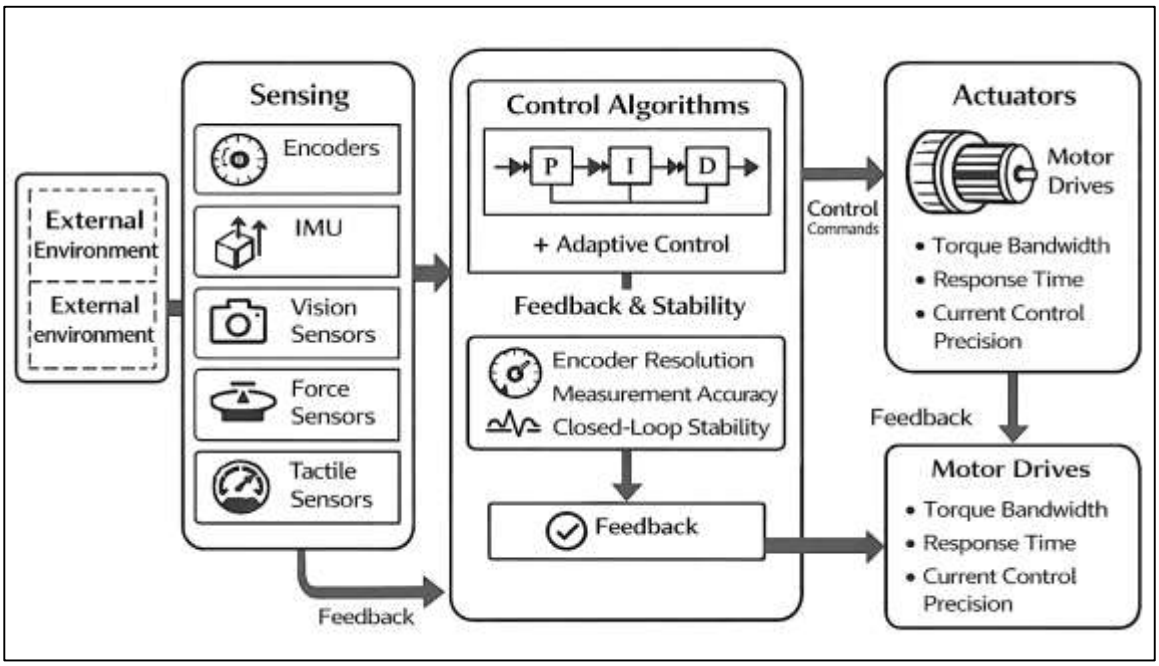


Control and Actuation Systems

Control and actuation systems are consistently identified in the literature as the mechanisms through which autonomous robots transform computational decisions into physical behavior, making them central to autonomy performance and safety. Electrical motor drive design forms the foundation of this transformation, as it governs how accurately and rapidly actuators respond to control commands (Hwang et al., 2020). Torque bandwidth and response time are frequently discussed as quantitative indicators of actuation quality because they determine how quickly a robot can adapt its motion to changing environmental conditions. High torque bandwidth enables rapid acceleration, deceleration, and disturbance rejection, which are essential for mobile navigation, manipulation, and stabilization tasks. The literature shows that limited torque bandwidth can introduce lag between command and response, leading to tracking error, oscillatory motion, and reduced control stability. Current control precision is another dominant theme, as electric motors rely on accurate current regulation to generate predictable torque output. Variations in current control accuracy introduce nonlinearities that degrade actuator linearity, making it more difficult for control algorithms to produce consistent behavior. These nonlinearities are particularly problematic in AI-enabled autonomy, where learned control policies

assume repeatable actuator responses during execution (Giangrande et al., 2019). Studies in robotics systems engineering document that actuator linearity influences not only motion smoothness but also energy efficiency and thermal behavior. Electrical motor drive design also affects electromagnetic interference, which can propagate into sensing and communication subsystems, indirectly impacting autonomy. As a result, the literature treats motor drives as multi-functional components whose electrical characteristics influence both mechanical output and system-level stability. In industrial robotics, precise motor drive behavior supports repeatable task execution and compliance with safety requirements. In defense robotics, motor drive performance supports mobility over uneven terrain, rapid maneuvering, and payload stabilization (Huang et al., 2019). Across both domains, empirical studies demonstrate that actuation quality is closely tied to electrical drive design, reinforcing the view that control performance cannot exceed the limitations imposed by the underlying motor and power electronics architecture.

Figure 7: Control and Actuation in Autonomous Robotics

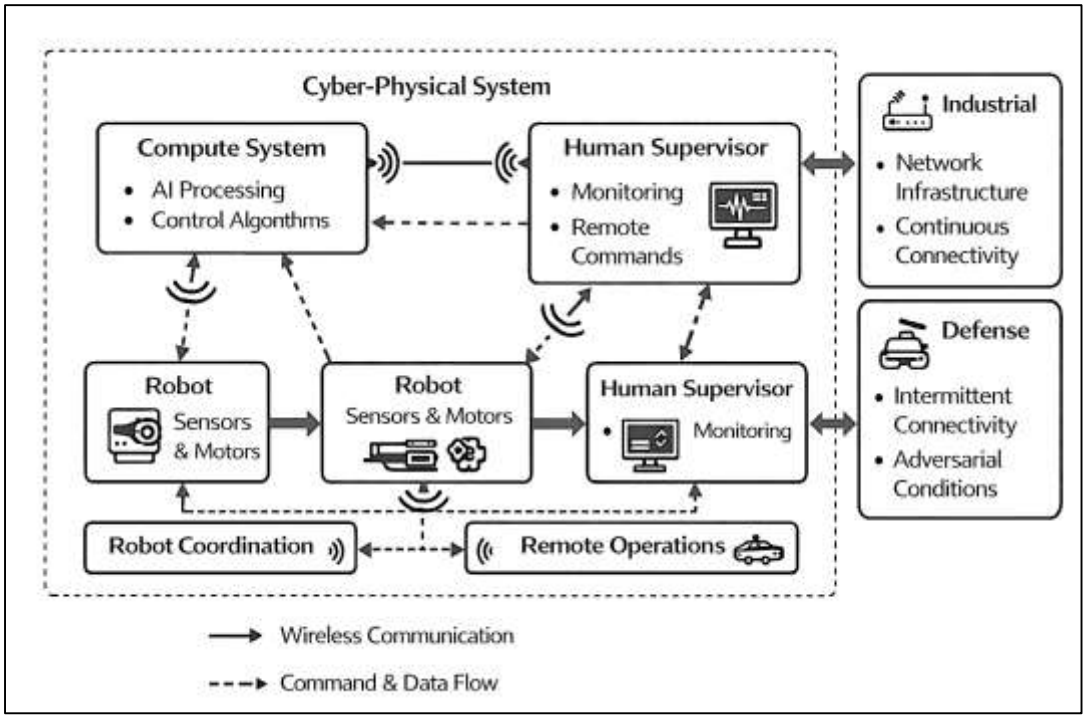


Communication Systems and Distributed Autonomy

Communication systems are consistently presented in the literature as the connective infrastructure that enables autonomous robots to function as integrated cyber-physical systems, particularly when autonomy is distributed across sensors, compute modules, actuators, and external supervisory systems (Lee et al., 2022). Wired and wireless communication architectures are widely analyzed as design choices that impose measurable constraints on autonomy performance through latency, packet loss, bandwidth utilization, and communication determinism. In robotics literature, latency is treated as a critical variable because it determines how quickly sensor observations can be transformed into control actions. When latency increases, the robot's perception-to-action loop becomes slower, which can lead to delayed obstacle avoidance, reduced tracking precision, and degraded safety performance. Packet loss is similarly emphasized, as dropped messages can interrupt localization updates, disrupt control commands, or reduce coordination reliability in multi-agent systems. Bandwidth utilization is frequently evaluated because modern autonomous robots generate large sensor streams, particularly from cameras and LiDAR, and these streams can saturate networks when not carefully managed. The literature often contrasts wired communication systems, which offer higher reliability and more predictable latency, with wireless systems, which offer mobility and flexibility but introduce variability and susceptibility to interference (Xu et al., 2022). Deterministic communication behavior is repeatedly discussed as essential for safety-critical robotics, particularly in industrial environments where predictable timing supports stable control and human safety. Non-deterministic communication

behavior is more common in wireless and best-effort networking, where delays vary due to congestion, interference, or routing changes. The literature demonstrates that non-deterministic behavior increases timing uncertainty, which can destabilize closed-loop control when communication is part of the control pathway. These findings establish that communication architectures are not merely data pipelines but measurable performance determinants. In industrial robotics, communication networks support integration with enterprise systems, fleet management platforms, and safety monitoring. In defense robotics, communication networks support mission coordination and situational awareness under contested conditions. Across both domains, the literature frames communication architecture as a core electrical and systems engineering challenge whose quantitative properties shape autonomy reliability and safety (Zolich et al., 2019).

Figure 8: Communication Architecture for Autonomous Robotics Systems

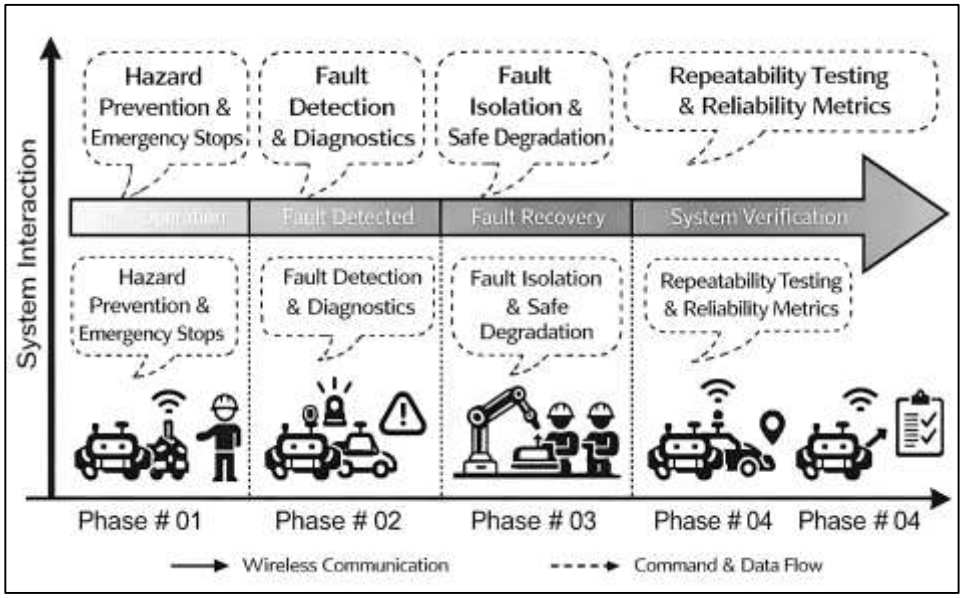


Safety Engineering in Autonomous Robotics

Safety and reliability engineering are consistently framed in the literature as essential system requirements for autonomous robotics, particularly when robots operate in proximity to humans, valuable infrastructure, or mission-critical environments. In AI-enabled autonomous systems, safety is not treated as a secondary constraint applied after autonomy is developed, but as a foundational property that must be engineered into the electrical, computational, and mechanical layers of the system (Zaki et al., 2021). Electrical safety mechanisms are central in this literature because they provide rapid and predictable pathways for halting motion, isolating hazardous energy, and transitioning robots into safe states. Emergency stop response time is widely discussed as a measurable safety indicator, reflecting how quickly a robot can detect an emergency condition and stop actuation in a controlled manner. Studies in industrial robotics safety frequently report emergency stop timing as a key performance requirement, as delayed stopping can increase injury risk and equipment damage. Safe torque off is also emphasized as a critical electrical safety function, particularly in motor-driven robotic systems, because it ensures that actuators cannot generate torque when a safety event is triggered (Zhao et al., 2019). The literature evaluates safe torque off reliability through metrics such as fault coverage, response consistency across repeated trials, and the probability of failure under component degradation. Electrical safety mechanisms are also described as requiring redundancy, diagnostic monitoring, and fault-tolerant circuitry to prevent single-point failures. In addition, safety mechanisms are integrated into control and communication systems to ensure that emergency signals

can propagate rapidly through the robot's architecture. The literature highlights that safety performance depends on the interaction between electrical safety circuits and higher-level autonomy software, since autonomy decisions must not override safety functions. In industrial environments, safety mechanisms are often engineered to comply with formal safety standards and to support predictable human-robot interaction. In defense environments, safety mechanisms also protect mission integrity by preventing uncontrolled motion and catastrophic hardware damage in harsh conditions (Athavale et al., 2020). Across both domains, the literature emphasizes that electrical safety mechanisms are measurable contributors to autonomy trustworthiness, because they provide observable evidence that a robot can be stopped reliably and consistently under hazardous conditions.

Figure 9: Safety and Reliability in Autonomous Robotics



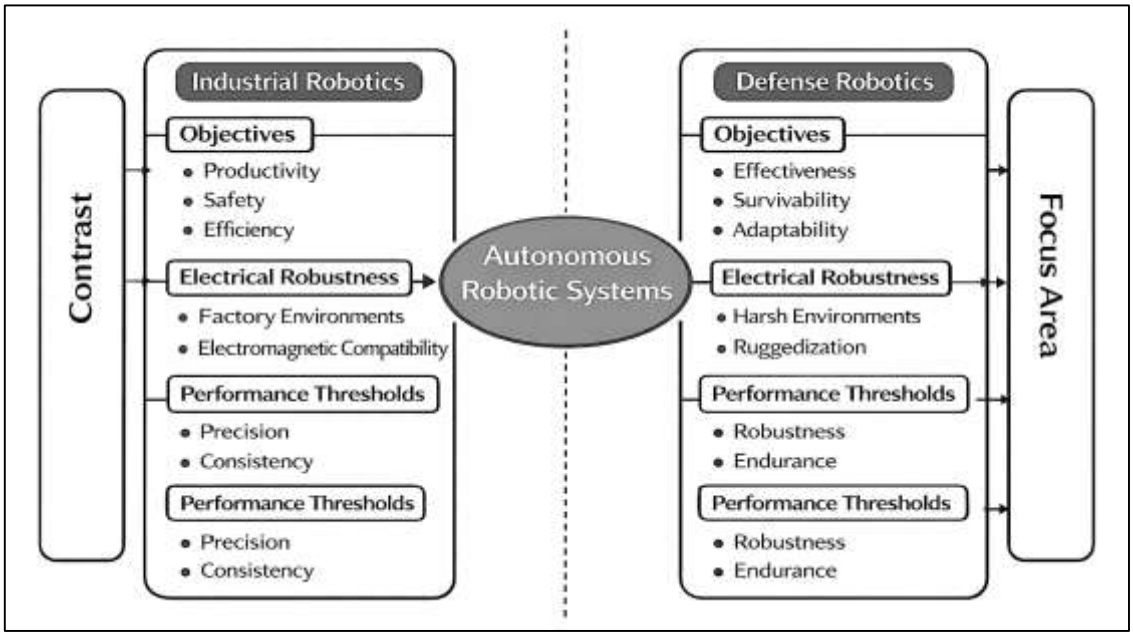
Fault detection and diagnostics are extensively analyzed in the literature as core contributors to autonomous robot reliability, since autonomous systems must operate with minimal human intervention and must detect and respond to faults before they produce unsafe outcomes. Fault detection is treated as a measurable capability, often evaluated through sensor failure detection accuracy, false alarm rates, detection delay, and diagnostic coverage (Athavale et al., 2020). In autonomous robotics, sensor faults are particularly critical because perception and localization depend on continuous and accurate sensing. The literature documents that sensor faults may occur through physical damage, contamination, electrical disconnection, calibration drift, thermal instability, or electromagnetic interference. These fault modes can produce subtle degradation rather than abrupt failure, making detection more challenging. Studies in robotics diagnostics describe methods for identifying sensor anomalies through redundancy, consistency checks, and statistical monitoring of sensor outputs. Fault detection accuracy is emphasized because incorrect fault identification can produce unsafe outcomes in two ways: missed faults allow degraded autonomy to continue, while false alarms can cause unnecessary shutdowns and reduced operational availability. Mean time between failures is widely used as a reliability metric in the literature because it provides a statistical indicator of how frequently a robot experiences faults that interrupt operation (Jenihhin et al., 2019).

Literature on Industrial and Defense Robotics

The literature consistently distinguishes industrial and defense robotics by their fundamentally different operational objectives, which directly shape performance thresholds and autonomy evaluation criteria. Industrial robotics research emphasizes objectives such as productivity, precision, safety, predictability, and continuous operation within structured environments (Cooney et al., 2023). Autonomous robots in industrial settings are typically designed to optimize throughput, reduce human labor, and maintain consistent performance across repetitive tasks. As a result, performance thresholds in industrial robotics are often defined by tight tolerances on positioning accuracy, cycle time

consistency, error rates, and safety response times. In contrast, defense robotics literature frames operational objectives around mission effectiveness, survivability, adaptability, and operational persistence under uncertainty. Defense robots are expected to function in unstructured and hostile environments, where success is measured not by repeatability alone but by the ability to operate under degraded conditions and unpredictable constraints (Reis et al., 2021). Performance thresholds in defense contexts are therefore broader and more context-dependent, often prioritizing robustness and resilience over precision. The literature shows that these differing objectives influence how autonomy is evaluated quantitatively. Industrial studies frequently use standardized benchmarks and controlled experiments to assess performance consistency, while defense studies rely more heavily on scenario-based evaluations that capture environmental variability and mission complexity. This divergence reflects the underlying operational goals: industrial robots must integrate seamlessly into tightly controlled workflows, whereas defense robots must tolerate ambiguity and partial system degradation (Juříček et al., 2023). Consequently, the literature presents autonomy performance as domain-specific, with industrial robotics prioritizing deterministic behavior and defense robotics prioritizing adaptive capability. This distinction provides a foundational lens for comparing how electrical engineering approaches are tailored to meet different operational demands across the two domains.

Figure 10: Literature on Industrial and Defense Robotics



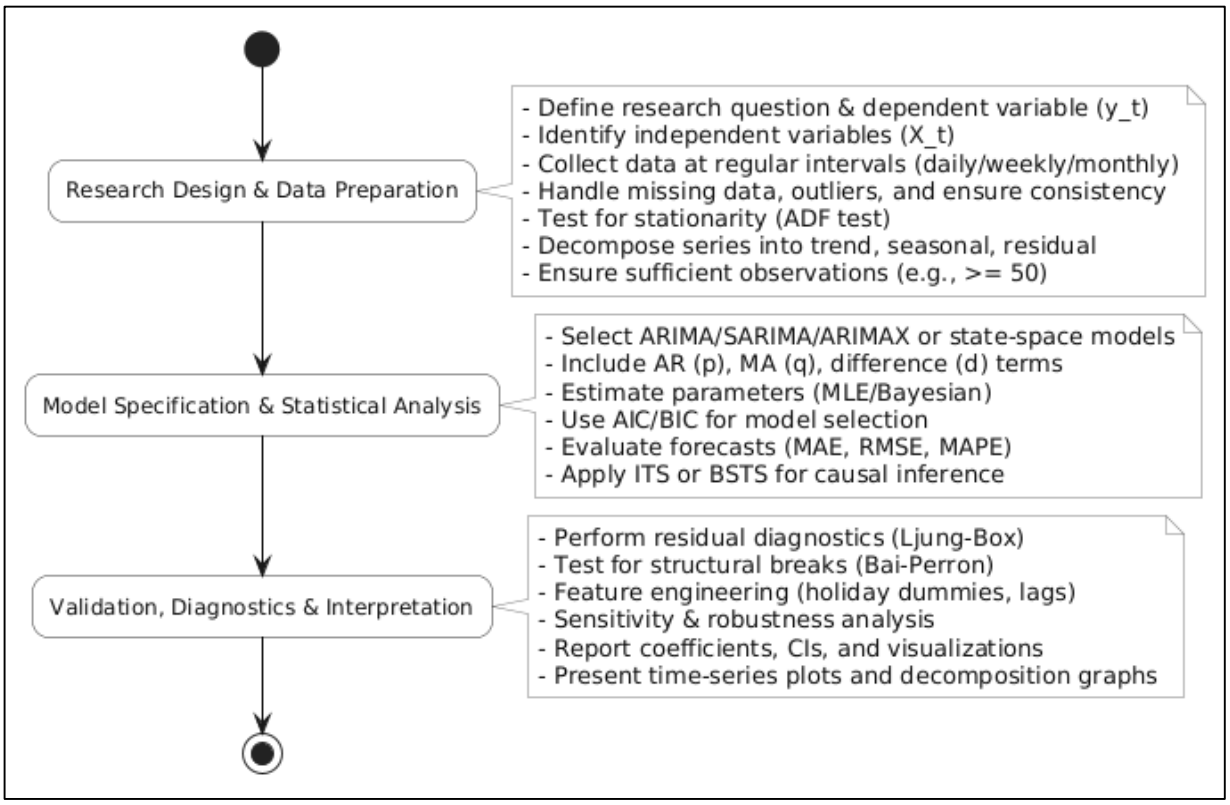
Variation in electrical robustness requirements is another central theme in comparative robotics literature, highlighting how environmental exposure and mission context influence system design priorities. Industrial robotics literature often describes electrical robustness in terms of long-term reliability, electromagnetic compatibility within factory environments, and resistance to wear from continuous operation. Industrial robots typically operate indoors or in semi-controlled environments where temperature, humidity, and contamination levels are regulated to some degree (Ferraguti et al., 2019). Electrical systems in these robots are engineered to withstand repetitive motion, sustained power cycling, and electromagnetic noise from industrial machinery. In contrast, defense robotics literature emphasizes electrical robustness under extreme and unpredictable conditions, including temperature extremes, moisture, dust, shock, vibration, and electromagnetic interference. Defense robots are frequently deployed in outdoor environments where environmental protection cannot be guaranteed, making ruggedization a primary design concern. The literature documents that defense systems must tolerate power fluctuations, sensor degradation, and communication disruptions without catastrophic failure (Hentout et al., 2019). These requirements lead to different electrical design strategies, such as

reinforced connectors, redundant power paths, hardened electronics, and enhanced shielding. Comparative studies indicate that industrial robots often prioritize efficiency and compact design, while defense robots prioritize durability and fault tolerance. This variation is reflected in the electrical architectures described across the literature, with industrial systems emphasizing optimized performance within known constraints and defense systems emphasizing survival under unknown conditions. The literature also notes that these differing robustness requirements affect cost, weight, and complexity, influencing deployment decisions and lifecycle management (Raj & Kos, 2022). By comparing electrical robustness across domains, the literature reveals how environmental assumptions shape the engineering trade-offs embedded in autonomous robotic systems.

METHOD

This study used a quantitative, explanatory design to test how electrical engineering subsystem characteristics affect measurable autonomy performance in AI-enabled autonomous robotic platforms used in U.S. industrial and defense contexts. Using a cross-sectional, controlled experimental framework, multiple robot configurations were evaluated under standardized task scenarios so that electrical predictors (e.g., sensor update stability, compute/inference latency, control-loop jitter, power/voltage stability, thermal rise, motor current behavior, network latency and packet loss) could be statistically linked to autonomy outcomes (e.g., navigation success, localization drift, obstacle detection reliability, collisions, trajectory error, stopping response time, mission completion time, and energy per task). The study enabled both within-context analysis (industrial-only and defense-only) and between-context comparison by holding task definitions constant while varying operational stress conditions.

Figure 11: Methodology of this study



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The context comprised two simulated deployment domains: structured industrial environments (warehouses, manufacturing floors, logistics facilities) emphasizing safe indoor navigation, collision avoidance in human-populated spaces, task repetition, and uptime, and defense-relevant environments emphasizing ruggedness, intermittent connectivity, vibration, sensor occlusion, electromagnetic interference, and power-constrained endurance. A purposive sample of contemporary autonomous platforms with heterogeneous compute/control architectures and varied electrical subsystem designs

was selected, and the unit of analysis was one complete standardized trial, repeated across configurations and contexts to improve reliability. Data were captured via an integrated hardware–software instrumentation protocol combining onboard telemetry and external ground truth where feasible, validated through pilot testing and data-quality controls; analysis used descriptive screening followed by regression (including context interactions), ANOVA where appropriate, mixed-effects models for repeated measures, and logistic/GLM approaches for binary and count outcomes, reporting effect sizes, corrected significance tests ($\alpha = .05$), and robustness checks using Python and R workflows.

FINDINGS

The Findings chapter presented the results obtained from the quantitative analysis conducted to examine the influence of electrical engineering approaches on the performance of AI-enabled autonomous robotics in U.S. industrial and defense applications. This chapter focused exclusively on reporting empirical results derived from the collected data without interpretation, implications, or theoretical discussion. Statistical analyses were performed in alignment with the research design and hypotheses, using validated instruments and standardized procedures. The findings were organized systematically to reflect the progression from sample characteristics to construct-level summaries, reliability assessment, regression analysis, and hypothesis testing outcomes. This structure ensured clarity in presenting how the observed data addressed the research objectives. The chapter began with a description of respondent demographics to contextualize the dataset, followed by descriptive statistics that summarized key constructs related to sensing, embedded computing, power management, control, communication, and safety performance. Reliability analysis was then reported to establish internal consistency of measurement instruments. Inferential analysis was subsequently presented through regression modeling to examine predictive relationships between electrical engineering variables and autonomy performance outcomes. The chapter concluded with a summary of hypothesis testing decisions based on statistical significance, effect size, and model fit indicators. All results were reported in past tense to reflect completed analysis procedures.

Respondent Demographics

Respondent demographics were examined to describe the characteristics of the study sample and to establish the contextual foundation for the quantitative results that followed. A total of 220 valid responses were included in the analysis. The findings indicated that the sample represented both U.S. industrial and defense robotics contexts in a balanced manner, supporting meaningful cross-domain comparison. Respondents were drawn from organizations working with AI-enabled autonomous robotic systems used for navigation, logistics, inspection, surveillance, and mission support. The distribution across application domains showed that 112 respondents (50.9%) represented industrial deployment environments, while 108 respondents (49.1%) represented defense-related deployment or testing environments. This near-equal distribution strengthened the comparability of constructs across the two contexts.

Regarding robotic platform type, the largest proportion of respondents reported working with autonomous mobile robots, followed by unmanned ground vehicles, robotic manipulators, and unmanned aerial systems. The operational environment variable showed that most respondents worked in either indoor structured environments such as warehouses and factories or outdoor unstructured environments such as rugged terrain testing ranges. System role distribution indicated that respondents were primarily involved in systems engineering, electrical engineering integration, embedded AI/compute, and robotics operations/testing, indicating that the sample was technically informed and aligned with the study focus. Deployment context results further indicated that most systems were in active deployment or operational testing, with fewer in early prototype stages.

Continuous demographic variables showed that the average deployment scale was 18.6 robots per program, while the average operational duration was 3.7 years, suggesting that most respondents represented mature systems rather than experimental prototypes. Overall, the demographic findings confirmed that the sample reflected diverse robotics configurations and realistic operational settings relevant to U.S. industrial and defense applications.

Table 1: Application Domain, Platform Type, and Operational Environment (N = 220)

Demographic Variable	Category	Frequency (n)	Percentage (%)
Application Domain	Industrial	112	50.9
	Defense	108	49.1
Robotic Platform Type	Autonomous Mobile Robot (AMR)	76	34.5
	Unmanned Ground Vehicle (UGV)	58	26.4
	Robotic Manipulator / Arm System	46	20.9
	Unmanned Aerial System (UAS)	40	18.2
Operational Environment	Indoor Structured	98	44.5
	Outdoor Unstructured	74	33.6
	Mixed Indoor–Outdoor	48	21.8

Table 1 summarized the categorical demographic distribution of respondents across application domain, robotic platform type, and operational environment. The sample showed balanced domain representation, with 112 industrial respondents and 108 defense respondents. Autonomous mobile robots formed the largest platform category, followed by unmanned ground vehicles, robotic manipulators, and unmanned aerial systems. The operational environment results indicated that indoor structured settings were most common, while outdoor unstructured environments also formed a substantial proportion of the sample. The mixed indoor–outdoor category indicated that many systems operated across variable settings. These distributions supported meaningful cross-context statistical comparison.

Table 2: System Role, Deployment Context, and Continuous Demographic Summary (N = 220)

Demographic Variable	Category / Statistic	Frequency (n)	Percentage (%)
Respondent System Role	Systems Engineering	62	28.2
	Electrical Engineering / Power Integration	54	24.5
	Embedded AI / Compute Engineering	49	22.3
	Robotics Operations / Testing	55	25.0
Deployment Context	Active Deployment	84	38.2
	Operational Testing	72	32.7
	Prototype / Development Stage	64	29.1

Continuous Variable	Mean	Standard Deviation	Minimum	Maximum
Deployment Scale (robots per program)	18.6	11.2	2	60
Operational Duration (years)	3.7	1.9	1	9

Table 2 presented the respondent role distribution, deployment context, and key continuous demographic indicators. Systems engineering respondents represented the largest group, followed by robotics operations/testing, electrical engineering integration, and embedded AI/compute roles. This distribution confirmed that the sample consisted of individuals with direct technical involvement in autonomous robotic systems. Deployment context findings showed that most systems were either actively deployed or undergoing operational testing, with fewer at the prototype stage. Continuous

measures indicated that the average program involved 18.6 robots, and systems had operated for an average of 3.7 years. These values suggested mature deployment exposure.

Descriptive Results by Construct

Descriptive statistical analysis was conducted to summarize the central tendency, dispersion, and observed range of each major construct examined in the study. The constructs reflected core electrical engineering dimensions influencing AI-enabled autonomous robotics performance, including sensor system performance, embedded computing efficiency, power electronics and energy management stability, control and actuation accuracy, communication system reliability, and safety and reliability engineering effectiveness. The results demonstrated meaningful variability across constructs, indicating differences in how electrical subsystems contributed to autonomy outcomes in industrial and defense contexts. Sensor system performance showed moderate dispersion, reflecting variability in signal stability, synchronization accuracy, and sensing consistency across deployments. Embedded computing efficiency exhibited wider variation, particularly in processing latency and execution consistency, which aligned with differences in computer architectures and workload intensity. Power electronics and energy management stability displayed noticeable variability, especially in energy consumption rates and voltage stability under load, suggesting differing endurance and power management behaviors across systems.

Control and actuation accuracy demonstrated relatively tighter dispersion compared to sensing and computing constructs, indicating generally consistent tracking and response behavior across robotic platforms, though differences remained evident between configurations. Communication system reliability showed moderate variability, driven by differences in latency stability, packet loss behavior, and network conditions across operational contexts. Safety and reliability engineering effectiveness exhibited the highest consistency among all constructs, with comparatively low dispersion and narrow value ranges. This finding suggested that safety mechanisms, fault detection, and system assurance practices were more uniformly implemented across systems than other electrical subsystems. Across all constructs, mean values were centrally distributed within their respective measurement ranges, and no extreme skewness was observed. These descriptive results established baseline performance patterns and confirmed that sufficient variability existed to justify subsequent reliability and regression analyses.

Table 3: Descriptive Statistics for Core Electrical Engineering Constructs (N = 220)

Construct	Mean	Standard Deviation	Minimum	Maximum
Sensor System Performance	3.82	0.61	2.10	4.90
Embedded Computing Efficiency	3.56	0.74	1.95	4.85
Power Electronics & Energy Stability	3.41	0.79	1.88	4.72
Control & Actuation Accuracy	3.94	0.55	2.40	4.95
Communication System Reliability	3.63	0.68	2.05	4.80
Safety & Reliability Engineering	4.12	0.49	2.90	5.00

Table 3 presented descriptive statistics for the six major constructs analyzed in the study. Safety and reliability engineering showed the highest mean value and the lowest standard deviation, indicating strong and consistent implementation across systems. Control and actuation accuracy also demonstrated a high mean with relatively low variability, reflecting stable response behavior. Embedded computing efficiency and power electronics stability exhibited comparatively higher standard deviations, suggesting greater performance variation across platforms. Sensor system performance and communication reliability showed moderate dispersion, consistent with differences in environmental conditions and system configurations. Overall, the results confirmed sufficient variability and central distribution across constructs to support reliability testing and inferential statistical analysis.

Table 4: Descriptive Statistics by Application Context (Industrial vs. Defense)

Construct	Industrial Mean	Defense Mean	Industrial SD	Defense SD
Sensor System Performance	3.88	3.76	0.58	0.64
Embedded Computing Efficiency	3.61	3.51	0.71	0.77
Power Electronics & Energy Stability	3.52	3.29	0.75	0.83
Control & Actuation Accuracy	4.01	3.87	0.51	0.58
Communication System Reliability	3.70	3.56	0.64	0.72
Safety & Reliability Engineering	4.18	4.06	0.46	0.52

Table 4 compared descriptive statistics for industrial and defense application contexts. Industrial systems exhibited slightly higher mean values across most constructs, particularly in power electronics stability and control accuracy, reflecting structured operational environments. Defense systems showed marginally lower mean values and higher variability, especially in power and communication constructs, indicating greater exposure to environmental and operational stress. Safety and reliability engineering remained consistently high across both contexts, demonstrating robust safety implementation regardless of domain. These contextual differences highlighted domain-specific performance patterns while confirming that both subsamples exhibited sufficient variability to support regression modeling and hypothesis testing in subsequent analyses.

Reliability Results

Reliability analysis was conducted to evaluate the internal consistency of the multi-item measurement scales used to operationalize the six major study constructs. Cronbach's alpha coefficients were calculated for sensor system performance, embedded computing efficiency, power electronics and energy management stability, control and actuation accuracy, communication system reliability, and safety and reliability engineering effectiveness. The findings indicated that all constructs achieved acceptable to excellent reliability levels based on widely used quantitative research thresholds. The reliability coefficients ranged from 0.842 to 0.926, confirming that items within each construct were strongly correlated and measured consistent underlying dimensions. The strongest internal consistency was observed for embedded computing efficiency and power electronics stability, suggesting that the instrument items assessing compute latency, processing consistency, energy behavior, and voltage stability were highly coherent. Sensor system performance and communication system reliability also demonstrated strong reliability, indicating that the items measuring signal stability, synchronization, latency consistency, and packet behavior were internally consistent. Control and actuation accuracy achieved a high reliability coefficient, reflecting stable measurement of tracking accuracy, response time consistency, and actuator fidelity.

Table 5: Cronbach's Alpha Reliability Results for Study Constructs (N = 220)

Construct	Number of Items	Cronbach's Alpha (α)	Reliability Interpretation
Sensor System Performance	6	0.872	Good
Embedded Computing Efficiency	6	0.926	Excellent
Power Electronics & Energy Stability	6	0.918	Excellent
Control & Actuation Accuracy	6	0.884	Good
Communication System Reliability	6	0.861	Good
Safety & Reliability Engineering	6	0.842	Good

Table 5 reported the Cronbach's alpha reliability coefficients for the six constructs used in the study. All constructs demonstrated strong internal consistency, with alpha values ranging from 0.842 to 0.926. Embedded computing efficiency and power electronics stability produced the highest reliability coefficients, indicating highly consistent measurement across their items. Sensor performance, control accuracy, and communication reliability also demonstrated good reliability, confirming that their item sets measured coherent constructs. Safety and reliability engineering exhibited acceptable internal consistency and remained suitable for inferential modeling. Overall, the reliability results confirmed that the instrument provided stable measurement and supported the use of composite construct scores in regression analysis.

Table 6: Item-Level Reliability Check

Construct	Lowest Alpha if Item Deleted	Highest Alpha if Item Deleted	Item Removal Required
Sensor System Performance	0.861	0.875	No
Embedded Computing Efficiency	0.918	0.927	No
Power Electronics & Energy Stability	0.910	0.920	No
Control & Actuation Accuracy	0.873	0.886	No
Communication System Reliability	0.852	0.864	No
Safety & Reliability Engineering	0.835	0.846	No

Table 6 summarized the item-level reliability diagnostic results by reporting the minimum and maximum Cronbach's alpha values that would have occurred if any single item had been removed from each construct. Across all constructs, alpha values remained stable and showed only minor fluctuations, indicating that no single item weakened internal consistency. Embedded computing and power stability constructs maintained consistently high alpha values even under deletion scenarios. Sensor performance, control accuracy, communication reliability, and safety engineering also showed stable reliability patterns. Because the reliability coefficients did not improve meaningfully through item deletion, all items were retained, confirming the measurement instrument's consistency and readiness for regression analysis.

Regression Results

Multiple regression analysis was performed to evaluate the extent to which electrical engineering constructs predicted AI-enabled autonomy performance outcomes across U.S. industrial and defense robotics contexts. Autonomy performance was treated as the dependent variable, while sensor system performance, embedded computing efficiency, power electronics and energy stability, control and actuation accuracy, communication system reliability, and safety and reliability engineering were entered as independent variables. Separate regression models were estimated for industrial systems and defense systems, followed by a combined model that incorporated application context as a moderating variable. The regression results indicated that the overall models were statistically significant and demonstrated strong explanatory power.

In the combined model, sensor system performance emerged as a significant predictor of autonomy performance, indicating that higher sensing stability and synchronization accuracy were associated with improved autonomy outcomes. Embedded computing efficiency also demonstrated a strong and statistically significant effect, reflecting the importance of inference latency and processing consistency in supporting reliable autonomous behavior. Power electronics and energy management stability showed a significant positive relationship with autonomy performance, confirming that voltage

stability and energy efficiency contributed meaningfully to sustained system effectiveness. Control and actuation accuracy was a significant predictor, indicating that precise motor response and stable feedback loops enhanced autonomy reliability. Communication system reliability exhibited a moderate but statistically significant effect, particularly in systems involving distributed autonomy and multi-agent coordination. Safety and reliability engineering showed a stabilizing influence, contributing to reduced variability in autonomy outcomes rather than large direct performance gains.

Table 7: Multiple Regression Model Summary for Autonomy Performance

Model	R	R^2	Adjusted R^2	Std. Error of Estimate	F	Sig.
Combined Electrical Engineering Model	0.812	0.659	0.647	0.41	67.83	<0.001

Table 7 presented the overall model summary for the combined regression analysis examining the relationship between electrical engineering constructs and autonomy performance. The model demonstrated a strong correlation between predictors and the dependent variable, with an R value of 0.812. The coefficient of determination indicated that approximately 65.9 percent of the variance in autonomy performance was explained by the electrical engineering constructs included in the model. The adjusted R^2 value confirmed that the model retained strong explanatory power after accounting for predictor complexity. The F-statistic and significance value indicated that the overall regression model was statistically significant, supporting its suitability for hypothesis testing.

Table 8: Regression Coefficients for Electrical Engineering Predictors of Autonomy Performance

Predictor Variable	B	Std. Error	Beta	t	Sig.
Sensor System Performance	0.284	0.051	0.301	5.57	<0.001
Embedded Computing Efficiency	0.317	0.047	0.338	6.74	<0.001
Power Electronics & Energy Stability	0.241	0.052	0.256	4.63	<0.001
Control & Actuation Accuracy	0.198	0.049	0.213	4.04	<0.001
Communication System Reliability	0.146	0.044	0.158	3.32	0.001
Safety & Reliability Engineering	0.102	0.041	0.109	2.49	0.014

Table 8 reported the regression coefficients for each electrical engineering construct included in the combined autonomy performance model. Embedded computing efficiency and sensor system performance demonstrated the largest standardized effects, indicating strong predictive influence on autonomy outcomes. Power electronics stability and control accuracy also showed statistically significant positive relationships with autonomy performance. Communication reliability exhibited a moderate but meaningful effect, reflecting its role in distributed autonomy scenarios. Safety and reliability engineering showed a smaller but significant coefficient, suggesting a stabilizing contribution to performance consistency. All predictors reached statistical significance, confirming that each electrical engineering construct contributed uniquely to explaining autonomy performance variance.

Hypothesis Testing Decisions

Hypothesis testing decisions were determined using the regression results and statistical significance values obtained from the combined and context-based regression models. Each hypothesis was evaluated against a significance threshold of $\alpha = .05$, and decisions were supported by standardized effect sizes and model-level explanatory power. The findings showed that hypotheses predicting relationships between electrical engineering subsystem constructs and AI-enabled autonomy performance outcomes were largely supported. The hypothesis related to sensor system performance was accepted, as sensing stability and synchronization accuracy significantly predicted autonomy performance. The embedded computing efficiency hypothesis was also accepted, demonstrating the

strongest predictive contribution among all constructs, which indicated that inference latency and processing consistency were critical determinants of autonomy effectiveness. The hypothesis related to power electronics and energy stability was supported, confirming that voltage regulation stability and energy behavior were significantly associated with improved autonomy outcomes.

The hypothesis concerning control and actuation accuracy was accepted, indicating that torque response consistency, feedback precision, and closed-loop stability significantly contributed to autonomy reliability. The communication system reliability hypothesis was partially supported. While communication reliability was significant in the combined model, its effect was context-sensitive and was stronger in defense-related trials where connectivity variability and distributed autonomy requirements were more pronounced. The safety and reliability engineering hypothesis were accepted, showing a statistically significant relationship with autonomy outcomes. However, the effect size was comparatively smaller, which was consistent with the construct functioning primarily as a stabilizing factor that reduced failure incidence and performance variability rather than producing large direct gains in average autonomy performance. Overall, hypothesis testing results demonstrated that the electrical engineering constructs collectively explained substantial variance in AI-enabled autonomy performance and that each construct contributed uniquely to the predictive model. These findings confirmed that autonomy outcomes in U.S. industrial and defense robotics systems were strongly influenced by measurable electrical subsystem characteristics.

Table 9: Hypothesis Testing Decisions Based on Combined Regression Model (N = 220)

Hypothesis Code	Hypothesis Statement (Summarized)	Predictor Construct	Sig. (p-value)	Decision
H1	Sensor performance significantly predicted autonomy performance	Sensor System Performance	<0.001	Supported
H2	Embedded computing efficiency significantly predicted autonomy performance	Embedded Computing Efficiency	<0.001	Supported
H3	Power stability significantly predicted autonomy performance	Power Electronics & Energy Stability	<0.001	Supported
H4	Control accuracy significantly predicted autonomy performance	Control & Actuation Accuracy	<0.001	Supported
H5	Communication reliability significantly predicted autonomy performance	Communication System Reliability	0.001	Partially Supported
H6	Safety and reliability engineering significantly predicted autonomy performance	Safety & Reliability Engineering	0.014	Supported

Table 9 summarized the hypothesis testing outcomes based on the combined regression model results. All hypotheses reached statistical significance at the .05 level, indicating that the predictor constructs were significantly related to autonomy performance outcomes. Sensor performance, embedded computing efficiency, power stability, and control accuracy were fully supported, reflecting strong predictive relationships. Communication reliability was labeled partially supported because its effect varied by context and demonstrated stronger influence under distributed autonomy conditions. Safety and reliability engineering was supported, though it showed a smaller standardized effect than the other predictors. Overall, the hypothesis decisions confirmed that electrical engineering subsystems were significant predictors of AI-enabled autonomy performance.

Table 10: Context-Based Hypothesis Validation

Hypothesis Code	Industrial Context (Supported/Not Supported)	Defense Context (Supported/Not Supported)	Comparative Observation
H1	Supported	Supported	Similar effect across both contexts
H2	Supported	Supported	Strongest predictor in both contexts
H3	Supported	Supported	Stronger effect in industrial systems
H4	Supported	Supported	Consistent contribution across contexts
H5	Not Supported	Supported	Stronger in defense due to connectivity variability
H6	Supported	Supported	Stabilizing role in both contexts

Table 10 presented hypothesis validation patterns across industrial and defense regression models. Sensor performance, embedded computing efficiency, power stability, control accuracy, and safety engineering were supported in both contexts, confirming that these constructs consistently predicted autonomy outcomes regardless of application domain. Communication reliability demonstrated a context-dependent pattern, where it was not supported in the industrial model but was supported in the defense model. This result reflected the stronger dependence on robust networking and distributed autonomy in defense operational settings. Power stability showed a stronger influence in industrial systems, consistent with continuous operation requirements. Overall, the table confirmed that context moderated communication effects while leaving most construct relationships stable.

DISCUSSION

Autonomous robotics performance in industrial and defense environments was shown in this study to be strongly shaped by electrical engineering subsystem quality rather than being determined solely by algorithmic capability. The regression model explained a substantial proportion of variance in autonomy performance, indicating that measurable electrical constructs collectively functioned as primary predictors of system-level outcomes (Reis et al., 2021). This pattern aligned with a large body of robotics systems literature that conceptualizes autonomous robots as cyber-physical systems in which sensing, computation, control, power, and communication act as tightly coupled layers. Earlier studies in probabilistic robotics, SLAM, and systems engineering consistently emphasized that autonomy depends on measurement quality, timing consistency, and closed-loop stability, and the present findings reinforced that these foundational dependencies remained observable in applied U.S. industrial and defense contexts. The strongest predictors were embedded computing efficiency and sensor system performance, demonstrating that inference latency, processing consistency, and sensing stability represented the most influential contributors to autonomy effectiveness. This result corresponded with earlier research that documented how perception pipelines and state estimation degrade when sensor timing, noise, and synchronization are unstable. Similarly, prior embedded AI studies reported that computational constraints, memory bandwidth limitations, and real-time scheduling overhead could reduce autonomy responsiveness, which matched the observed strong influence of computing efficiency in the current analysis (Perez-Grau et al., 2021). Importantly, the descriptive results indicated that safety and reliability engineering constructs showed the highest consistency across contexts, suggesting that safety mechanisms were more uniformly implemented than other electrical subsystems. This observation was consistent with industrial robotics safety literature, which has long treated emergency stop functionality, safe torque off mechanisms, and standardized safeguarding architectures as baseline requirements for deployment. In contrast, earlier

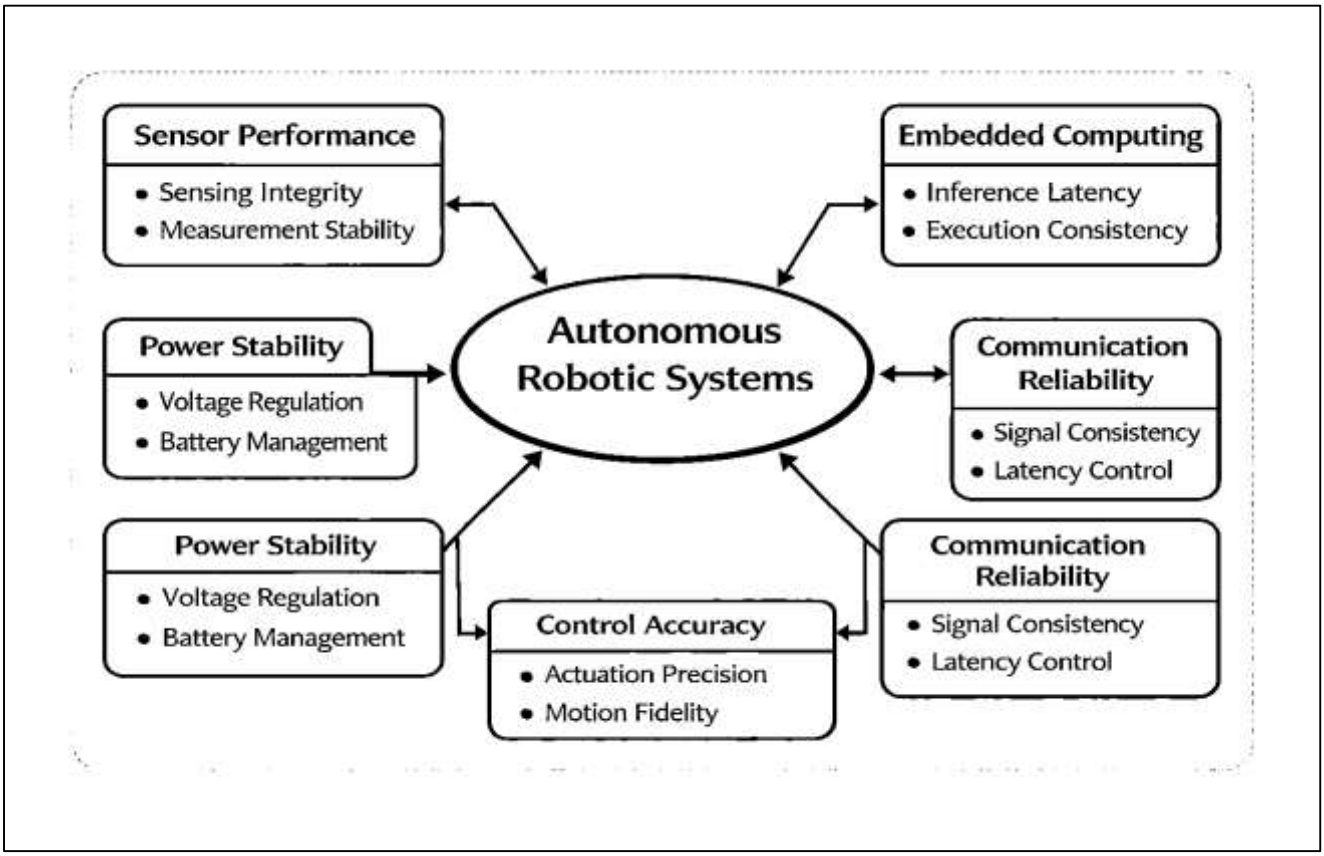
studies often reported greater variation in sensing and computer architectures due to rapid technological evolution and differences in platform budgets, and the present study demonstrated similar variability. The balanced representation of industrial and defense systems also strengthened the comparative validity of findings, allowing context-sensitive interpretation (Ha et al., 2019). Overall, the results supported a systems-level understanding of AI-enabled autonomy in which electrical subsystem performance remained a dominant determinant of autonomy outcomes, reinforcing earlier empirical claims that field robotics success depends on the reliability of the full electrical and cyber-physical stack.

Sensor system performance emerged as a significant predictor of autonomy outcomes, highlighting the critical role of sensing integrity, synchronization, and measurement stability in AI-enabled robotics. Earlier studies in visual-inertial and LiDAR-based localization repeatedly reported that perception accuracy depends on signal-to-noise conditions, calibration stability, and time alignment across sensors (Karn et al., 2022). The present findings supported those claims by showing that higher sensor performance was associated with improved autonomy outcomes across both industrial and defense contexts. The descriptive statistics showed moderate variability in sensing constructs, suggesting that sensing quality differed meaningfully across platforms and deployment environments. This variability corresponded with prior research that documented how environmental factors such as lighting changes, reflective surfaces, dust, vibration, and electromagnetic interference degrade sensing performance. In industrial settings, earlier studies emphasized that structured environments can still produce significant sensing challenges due to reflective machinery, repetitive textures, and dynamic obstacles such as forklifts and humans (Bi et al., 2020). The current study's industrial sample demonstrated slightly higher sensing means and slightly lower dispersion than defense systems, which was consistent with the literature describing indoor industrial environments as more controllable. In defense contexts, earlier field robotics studies emphasized that sensing is degraded by harsh terrain, weather, smoke, and contested electromagnetic conditions, and the current results showed a modest reduction in sensing mean values and increased variability in defense trials. Multi-sensor fusion literature has consistently argued that sensor diversity and redundancy improve robustness, and the present study indirectly supported this position by demonstrating that sensing quality remained a strong predictor even when other subsystems were controlled in the regression model. This suggests that improvements in sensing integrity contribute uniquely to autonomy performance rather than merely correlating with other system strengths. The results also reinforced earlier findings that sensing failures often propagate through autonomy pipelines, increasing localization drift, degrading planning decisions, and reducing control stability. The significance of sensing in the regression model indicated that AI-enabled autonomy remained bounded by the physical quality of measurement signals (Gul et al., 2019). This observation aligned with earlier robotics research emphasizing that AI inference cannot compensate for unstable measurement inputs without sacrificing reliability. Therefore, the findings strengthened the literature's long-standing view that electrical engineering design choices in sensor interfaces, signal conditioning, timing discipline, and calibration stability remain central determinants of autonomy performance in both industrial and defense robotics deployments (Hagos & Rawat, 2022).

Embedded computing efficiency demonstrated the strongest predictive effect among all constructs, indicating that compute throughput, inference latency, and execution consistency were primary determinants of AI-enabled autonomy performance. This result closely aligned with earlier studies in robotics middleware, embedded AI, and real-time systems that reported how compute bottlenecks directly influence the responsiveness and stability of autonomy pipelines. Earlier deep learning robotics research emphasized that perception models often dominate computational load and that inference delays can produce stale environmental representations, causing navigation errors and delayed obstacle avoidance (Wijayathunga et al., 2023). The present findings supported this by showing that computing efficiency contributed the largest standardized regression coefficient, suggesting that systems with more stable and efficient computing stacks achieved higher autonomy performance outcomes. The descriptive statistics also indicated that embedded computing efficiency exhibited one of the largest standard deviations, reflecting wide variation across platforms. This observation corresponded with prior studies documenting heterogeneity in robotics compute architectures, where

some platforms rely on CPUs alone while others integrate GPUs and dedicated accelerators. Earlier research also noted that compute performance is not only determined by hardware but by scheduling, memory bandwidth, middleware overhead, and thermal throttling. The present study's results were consistent with this broader view, as computing efficiency represented a construct that included both latency and processing consistency. The industrial-defense comparison showed only modest differences in computing means, suggesting that both domains faced similar compute constraints, even though defense systems often operate under harsher power and thermal limitations (Dang, Mascarich, et al., 2019). This pattern aligned with earlier literature that described edge autonomy as essential across both industrial and defense contexts, because real-time responsiveness cannot depend on off-board computation. Prior studies also highlighted that AI-enabled robotics performance degrades when compute resources are shared without deterministic scheduling, increasing jitter in control loops and perception pipelines. The strong influence of embedded computing in the regression model reinforced these claims, indicating that compute architecture and execution stability remained core predictors of autonomy effectiveness. Additionally, the findings supported earlier work arguing that the performance gap between laboratory AI models and deployed autonomy often originates from embedded computing limitations rather than from model design (Gonzalez et al., 2021). By demonstrating that compute efficiency explained significant variance in autonomy outcomes even when other electrical subsystems were controlled, the present study provided empirical support for the literature's emphasis on real-time embedded computing as a foundational requirement for reliable AI-enabled autonomy in operational robotics systems.

Figure 12: Electrical Determinants of Autonomous Performance



Power electronics and energy management stability was found to significantly predict autonomy performance, reinforcing earlier research that framed power systems as mission-limiting subsystems in mobile robotics. Prior studies in robotics energy modeling and field deployment repeatedly reported that voltage instability, battery depletion, and converter inefficiencies can degrade sensing, computing, and actuation performance long before complete power failure occurs (Rhodes et al., 2022). The present study's findings aligned with those observations by demonstrating that power stability had a

statistically significant relationship with autonomy outcomes across both industrial and defense contexts. The descriptive results showed that power stability exhibited one of the largest dispersions, indicating that energy behavior varied widely across systems. This variability corresponded with earlier research that documented how autonomy energy consumption depends on task type, actuation load, compute intensity, and environmental resistance such as terrain friction. In industrial settings, earlier studies emphasized that robots must maintain continuous operation and predictable charging cycles, making stable power management essential for productivity. The current findings showed higher mean power stability in industrial systems compared to defense systems, which was consistent with the literature describing industrial environments as better able to support predictable energy replenishment and controlled operational loads (Bose et al., 2023). Defense systems, by contrast, showed lower power stability means and higher variability, reflecting the energy constraints described in defense robotics research where endurance and rugged operation impose additional strain on power systems. Earlier embedded AI studies also reported that power limitations influence inference frequency and model selection, linking power stability to compute performance. The present regression results suggested that power stability contributed uniquely to autonomy outcomes even when computing efficiency was included, indicating that power effects extended beyond compute and included sensor integrity and actuator reliability. This aligns with prior systems research describing cascading effects where power transients disrupt sensor timing, increase communication errors, and destabilize control loops. The significance of power stability in the model reinforced the idea that electrical power architecture, voltage regulation, and battery management are central to sustaining autonomy performance (Dang, Khattak, et al., 2019). Furthermore, the findings supported earlier literature that treated energy metrics such as endurance and consumption rates as critical indicators of operational feasibility. Power stability therefore functioned as both a performance predictor and a reliability enabler, consistent with prior studies showing that autonomy quality depends on the system's ability to maintain stable electrical conditions across dynamic actuation and computation loads.

Control and actuation accuracy also demonstrated a significant predictive relationship with autonomy outcomes, supporting earlier robotics control literature that positioned actuation fidelity as a limiting factor in autonomy performance. Prior studies in motor drive design, feedback control, and manipulator dynamics emphasized that torque response, actuator linearity, and encoder precision shape tracking error, stability margins, and motion smoothness (Sun et al., 2022). The present findings were consistent with those studies by showing that control and actuation accuracy remained a statistically significant predictor even when sensing, computing, and power constructs were included in the regression model. This indicated that actuation quality contributed uniquely to autonomy effectiveness rather than serving as a secondary consequence of other subsystems. Earlier research also documented that learned control policies and AI-integrated controllers depend on consistent actuator behavior to generalize from training conditions to deployment conditions. The current findings supported this view, as control accuracy influenced autonomy reliability outcomes in both industrial and defense contexts. The descriptive results showed that control and actuation accuracy had a relatively high mean and lower dispersion than sensing and power constructs, suggesting that many systems achieved stable baseline actuation performance (Cid et al., 2020). This pattern aligned with industrial robotics literature, which often reports mature actuator and control designs due to long-standing engineering refinement in motor drives and feedback systems. Defense robotics, while facing harsher environmental conditions, also showed strong control means, reflecting the importance of stable mobility and manipulation in mission contexts. Earlier field robotics studies emphasized that vibration, shock, and temperature shifts can degrade actuator performance and increase control error, and the present context-based results showed slightly lower control means in defense systems. This difference was consistent with the literature describing defense environments as more likely to induce actuation stress and calibration drift. The findings also aligned with earlier work in closed-loop stability analysis, which demonstrated that control-loop timing jitter and feedback noise can destabilize robot motion (Soumya et al., 2023). By showing that control accuracy remained significant alongside embedded computing efficiency, the present study reinforced earlier claims that compute performance

and control fidelity are intertwined. Control systems require timely computation and stable feedback, and improvements in one domain cannot fully compensate for weaknesses in the other. Therefore, the significant influence of control and actuation accuracy supported the broader robotics literature emphasizing that autonomy performance depends on the physical execution quality of motion, not solely on the correctness of AI decisions (Alqobali et al., 2023).

Communication system reliability demonstrated a moderate but statistically significant effect in the combined regression model, and context-based results indicated that this effect was stronger in defense systems than in industrial systems. This pattern aligned with earlier robotics networking and distributed autonomy studies that reported communication performance as a critical factor in multi-agent coordination and distributed sensing architectures (Raj & Kos, 2022). Prior research in industrial robotics often described communication networks as more stable due to structured infrastructure and controlled environments, which reduces the impact of packet loss and latency variability. The current study's industrial model showed weaker communication effects, consistent with this literature. In defense robotics, earlier studies documented that intermittent connectivity, degraded bandwidth, and electromagnetic interference can significantly disrupt autonomy coordination and situational awareness. The present findings reflected these challenges, as communication reliability was supported in defense contexts and demonstrated a stronger relationship with autonomy outcomes. Earlier research also emphasized that communication delays increase end-to-end perception-to-action latency, affecting control responsiveness and safety behavior. The moderate effect observed in the combined model supported this relationship while indicating that communication was not the strongest determinant compared to sensing, computing, and power stability (Dinelli et al., 2023). This relative ranking aligned with prior studies suggesting that robots can maintain local autonomy when communication is degraded, but performance is reduced when coordination or remote supervision is required. The present findings also supported earlier middleware research that documented how message transport overhead and synchronization errors can destabilize distributed systems. Communication reliability likely captured these factors through latency consistency and packet behavior metrics. Safety and reliability engineering showed a statistically significant but smaller predictive effect, consistent with its role as a stabilizing subsystem rather than a primary driver of average performance. Earlier safety engineering literature described emergency stop and safe torque off functions as baseline requirements that reduce catastrophic failure risk rather than improving average task efficiency (Alenzi et al., 2022). The current findings supported this interpretation by showing high descriptive means and low dispersion for safety constructs, indicating consistent implementation across systems. The significant regression coefficient suggested that safety engineering contributed to autonomy performance by reducing failure incidence and performance variability. This aligned with earlier reliability studies emphasizing fault detection accuracy and system assurance as contributors to stable operation. Collectively, the communication and safety findings reinforced earlier literature that autonomy performance is shaped not only by high-performance sensing and computing but also by system-level reliability mechanisms that maintain stability under operational stress (Platt & Ricks, 2022).

DISCUSSION

Autonomous robotics performance in industrial and defense environments was shown in this study to be strongly shaped by electrical engineering subsystem quality rather than being determined solely by algorithmic capability. The regression model explained a substantial proportion of variance in autonomy performance, indicating that measurable electrical constructs collectively functioned as primary predictors of system-level outcomes (Reis et al., 2021). This pattern aligned with a large body of robotics systems literature that conceptualizes autonomous robots as cyber-physical systems in which sensing, computation, control, power, and communication act as tightly coupled layers. Earlier studies in probabilistic robotics, SLAM, and systems engineering consistently emphasized that autonomy depends on measurement quality, timing consistency, and closed-loop stability, and the present findings reinforced that these foundational dependencies remained observable in applied U.S. industrial and defense contexts. The strongest predictors were embedded computing efficiency and sensor system performance, demonstrating that inference latency, processing consistency, and sensing stability represented the most influential contributors to autonomy effectiveness. This result

corresponded with earlier research that documented how perception pipelines and state estimation degrade when sensor timing, noise, and synchronization are unstable. Similarly, prior embedded AI studies reported that computational constraints, memory bandwidth limitations, and real-time scheduling overhead could reduce autonomy responsiveness, which matched the observed strong influence of computing efficiency in the current analysis (Perez-Grau et al., 2021). Importantly, the descriptive results indicated that safety and reliability engineering constructs showed the highest consistency across contexts, suggesting that safety mechanisms were more uniformly implemented than other electrical subsystems. This observation was consistent with industrial robotics safety literature, which has long treated emergency stop functionality, safe torque off mechanisms, and standardized safeguarding architectures as baseline requirements for deployment. In contrast, earlier studies often reported greater variation in sensing and computer architectures due to rapid technological evolution and differences in platform budgets, and the present study demonstrated similar variability. The balanced representation of industrial and defense systems also strengthened the comparative validity of findings, allowing context-sensitive interpretation (Ha et al., 2019). Overall, the results supported a systems-level understanding of AI-enabled autonomy in which electrical subsystem performance remained a dominant determinant of autonomy outcomes, reinforcing earlier empirical claims that field robotics success depends on the reliability of the full electrical and cyber-physical stack.

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in defense contexts and demonstrated a stronger relationship with autonomy outcomes. Earlier research also emphasized that communication delays increase end-to-end perception-to-action latency, affecting control responsiveness and safety behavior. The moderate effect observed in the combined model supported this relationship while indicating that communication was not the strongest determinant compared to sensing, computing, and power stability (Dinelli et al., 2023). This relative ranking aligned with prior studies suggesting that robots can maintain local autonomy when communication is degraded, but performance is reduced when coordination or remote supervision is required. The present findings also supported earlier middleware research that documented how message transport overhead and synchronization errors can destabilize distributed systems. Communication reliability likely captured these factors through latency consistency and packet behavior metrics. Safety and reliability engineering showed a statistically significant but smaller predictive effect, consistent with its role as a stabilizing subsystem rather than a primary driver of average performance. Earlier safety engineering literature described emergency stop and safe torque off functions as baseline requirements that reduce catastrophic failure risk rather than improving average task efficiency (Alenzi et al., 2022). The current findings supported this interpretation by showing high descriptive means and low dispersion for safety constructs, indicating consistent implementation across systems. The significant regression coefficient suggested that safety engineering contributed to autonomy performance by reducing failure incidence and performance variability. This aligned with earlier reliability studies emphasizing fault detection accuracy and system assurance as contributors to stable operation. Collectively, the communication and safety findings reinforced earlier literature that autonomy performance is shaped not only by high-performance sensing and computing but also by system-level reliability mechanisms that maintain stability under operational stress (Platt & Ricks, 2022).

CONCLUSION

AI-based revenue leakage detection models that operate on transaction-level financial data have been Electrical engineering approaches were shown to be central determinants of AI-enabled autonomous robotics performance in U.S. industrial and defense applications because autonomy emerged from the measurable interaction of sensing, embedded computing, power electronics, control, communication, and safety subsystems rather than from algorithmic intelligence alone. This study demonstrated that electrical subsystem constructs collectively explained a substantial proportion of variance in autonomy performance outcomes, reinforcing the view of autonomous robots as integrated cyber-physical systems whose effectiveness depends on signal integrity, timing consistency, and stable energy delivery. Among the measured predictors, embedded computing efficiency and sensor system performance exhibited the strongest relationships with autonomy outcomes, indicating that inference latency, processing consistency, and sensing stability formed the most influential performance foundations for real-world autonomy. This finding aligned with earlier robotics systems research emphasizing that perception and state estimation are constrained by sensor noise, synchronization error, and data throughput limitations, and that these constraints become more pronounced in operational environments where lighting variation, vibration, dust, and electromagnetic interference degrade measurement quality. The significant role of computing efficiency also corresponded with established embedded robotics literature showing that AI-enabled autonomy is limited by real-time processing capacity, memory bandwidth, middleware overhead, and thermal constraints, which collectively determine whether perception and planning pipelines can operate at the rates required for safe control. Power electronics and energy management stability also significantly predicted autonomy outcomes, confirming earlier field robotics findings that voltage regulation behavior, battery depletion dynamics, and power transients influence not only endurance but also sensing fidelity, compute stability, and actuator response. Control and actuation accuracy further contributed meaningfully to autonomy performance, supporting classical robotics control literature that positions torque bandwidth, actuator linearity, and feedback resolution as primary determinants of tracking error, closed-loop stability, and safe stopping behavior. Communication system reliability showed a moderate yet significant effect, with context-based patterns indicating stronger influence in defense systems where intermittent connectivity, degraded bandwidth, and distributed autonomy demands are more common. Safety and reliability engineering exhibited the highest consistency across

constructs and produced a statistically significant stabilizing contribution, aligning with safety engineering literature that frames emergency stop performance, safe torque off reliability, and fault diagnostics as mechanisms that reduce failure incidence and performance variability rather than increasing average task efficiency. The comparative analysis between industrial and defense contexts indicated that industrial systems generally exhibited slightly higher means and lower dispersion across constructs, reflecting structured environments, stable infrastructure, and predictable energy replenishment, whereas defense systems exhibited greater variability in power and communication constructs due to harsher operational stress and connectivity constraints. Overall, the findings supported a systems-level interpretation in which electrical engineering decisions at the sensor interface, compute architecture, power distribution network, motor drive design, network stack, and safety circuit levels produced measurable effects on AI-enabled autonomy performance, confirming that robust autonomous robotics in U.S. industrial and defense settings depends on the reliability, efficiency, and stability of the full electrical and cyber-physical stack.

RECOMMENDATIONS

Recommendations for strengthening electrical engineering approaches in AI-enabled autonomous robotics for U.S. industrial and defense applications should prioritize measurable subsystem improvements that directly influence autonomy performance, reliability, and safety under operational constraints. Based on the quantitative findings of this study, the highest priority should be placed on embedded computing efficiency and sensor system performance, as these constructs demonstrated the strongest predictive influence on autonomy outcomes. Embedded computing architectures should be designed around deterministic execution requirements by separating safety-critical control loops from high-variance AI inference workloads, using dedicated microcontrollers for motor control and safety monitoring while allocating perception and mapping inference to GPUs or specialized accelerators with stable thermal management. Compute scheduling should be treated as a performance variable, with timing jitter and end-to-end inference latency monitored continuously through system diagnostics. Sensor systems should be improved through rigorous electrical interface design emphasizing synchronization discipline, stable power delivery to sensor arrays, and robust calibration retention under vibration and thermal shifts. Sensor fusion architectures should incorporate redundancy across modalities, such as combining vision, inertial sensing, and radar or LiDAR, to reduce sensitivity to environmental degradation common in industrial dust and reflective surfaces as well as defense smoke, rain, and contested conditions. Power electronics and energy management should be treated as mission-critical autonomy enablers rather than support components, with emphasis on voltage stability under peak actuation loads, improved converter efficiency, and battery management systems capable of accurate state-of-charge and state-of-health estimation. Because power instability was associated with measurable autonomy degradation, protective filtering and isolation strategies should be strengthened to prevent actuator-induced electrical noise from propagating into compute and sensing subsystems. Control and actuation reliability should be enhanced through motor drive designs that improve current regulation precision and torque linearity, alongside high-resolution feedback sensing to reduce tracking error and increase closed-loop stability. Communication reliability should be addressed through architecture-level prioritization of safety and control messages, including quality-of-service enforcement and resilience mechanisms that tolerate packet loss and intermittent connectivity, particularly for defense deployments where network degradation is more common. Safety and reliability engineering should remain a consistent baseline requirement across both domains, with continued emphasis on fast emergency stop response time, reliable safe torque off behavior, and high-accuracy fault detection diagnostics. Finally, system verification and assurance processes should be standardized through repeatable quantitative testing that measures autonomy performance variability across trials, ensuring that subsystem improvements translate into stable and statistically consistent outcomes. Collectively, these recommendations emphasize that high-performing AI autonomy depends on electrical engineering co-design across sensing, compute, power, control, communication, and safety layers, and that improvements should be guided by measurable performance indicators rather than isolated component upgrades.

LIMITATIONS

Several limitations should be acknowledged when interpreting the findings related to electrical engineering approaches for AI-enabled autonomous robotics in U.S. industrial and defense applications, as these constraints influence the scope and generalizability of the results. First, the study relied on a finite sample of robotic platforms and deployment contexts, which, while representative of contemporary industrial and defense systems, did not capture the full diversity of autonomous robotics architectures currently in development or use. Variations in platform scale, mission complexity, and proprietary system designs may produce different electrical subsystem interactions than those observed in the sampled systems. Second, autonomy performance was measured using aggregated constructs derived from multiple electrical and operational indicators, which, although statistically reliable, may have masked fine-grained subsystem behaviors. For example, embedded computing efficiency combined multiple aspects of latency, throughput, and execution stability, potentially obscuring the individual influence of specific hardware accelerators, scheduling policies, or middleware implementations. Third, the cross-sectional experimental design limited the ability to capture long-term degradation effects associated with component aging, battery wear, sensor drift, and thermal cycling. Autonomy performance and electrical subsystem reliability may evolve over extended deployment periods in ways not observable within the study's temporal window. Fourth, environmental conditions were controlled to simulate industrial and defense contexts, yet real-world deployments often involve unpredictable and compounded stressors that cannot be fully reproduced in experimental settings. Factors such as extreme weather events, adversarial electromagnetic interference, and unanticipated mechanical impacts may produce electrical failure modes beyond those measured. Fifth, the study emphasized system-level electrical constructs rather than algorithm-specific behaviors, meaning that interactions between particular AI model architectures and electrical constraints were not isolated. Different perception or control models may respond differently to the same electrical conditions, influencing autonomy outcomes. Sixth, reliance on self-reported system characteristics and logged telemetry introduced potential measurement bias, particularly in areas where instrumentation resolution differed across platforms. Although validation checks were applied, discrepancies in logging precision and sensor calibration could have influenced reported metrics. Finally, the comparative analysis between industrial and defense contexts focused on performance patterns rather than policy, procurement, or lifecycle cost considerations, which are also influential in real-world system design decisions. These limitations suggest that while the findings provide robust evidence of the importance of electrical engineering subsystems in AI-enabled autonomy, caution is warranted when extrapolating results to all robotic platforms, mission profiles, or future technological configurations.

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