Integrating SQA into the Robotic Software Development Lifecycle

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ABSTRACT

Software Quality Assurance (SQA) is integrated into the robotic software development lifecycle to improve robotic system dependability, safety, and performance in this research. The main goals are finding gaps in existing SQA procedures, presenting a specialized SQA integration architecture, and solving robotics difficulties, including hardware-software Integration, real-time processing, and machine learning validation; the research evaluates current SQA methodologies and proposes changes using secondary data from the literature, industry reports, and technical publications. Due to their intricate interconnections, hardware-in-the-loop (HIL) testing, real-time performance assessments, and automated Testing are crucial to the robotic system SQA. The report also notes resource requirements for extensive testing and simulation fidelity. Policy implications include standardizing testing techniques, investing in new simulation technology, and establishing safety and compliance regulations. The suggested paradigm addresses these difficulties to help design more dependable and competent robotic systems, improving robotics and its applications.

Keywords: Software Quality Assurance (SQA), Robotic Software, Development Lifecycle, Automation, Testing Strategies, Software Reliability, Quality Management

INTRODUCTION

Rapid advances in robotics technology have altered industry and healthcare, boosting autonomous system capabilities. Robot software has gotten more complicated as robots become more intelligent and essential to critical tasks. This transition highlights the need for adequate robotic software development-specific software quality assurance (SQA) techniques. SQA in robotic software development is no longer a recommendation but a need for dependability, safety, and performance (Addimulam et al., 2020).

Robotic systems work in low-error conditions. Robotic software interacts directly with the natural environment, demanding accuracy and durability considerably beyond typical applications (Ying et al., 2022). In the worst cases, robotic system failures may cause

operational delays, financial loss, and human safety risks. Thus, robotic software quality is crucial. However, SQA incorporation into robotic software development brings distinct obstacles. Robotic systems need real-time processing, agility, and the capacity to perform in uncertain contexts, so traditional SQA methods may fail to meet their objectives. Hardware and software components work closely during robotic software development, making it more iterative and interdisciplinary (Anumandla et al., 2020). Due to these issues, conventional SQA methods must be rethought for robots.

This Integration requires adapting SQA approaches to robotic systems' hybrid nature, which frequently combines software, hardware, and human interaction. Due to their complexity, SQA methods must address software correctness, performance, and interaction with the robot's physical components and operating environment (Deming et al., 2021). Testing methodologies must examine how software upgrades may influence robot mechanical components or how environmental changes affect system behavior. Continuous Integration and Testing are other essential features of SQA in robotic software development. Since robotic software development is iterative and components are often updated and improved, continual SQA procedures guarantee quality (Mohammed et al., 2017). This method detects faults early, lowers repair costs, and assures the product fulfills safety and performance criteria. SQA is further complicated by robotic software's dynamic nature, which may include machine learning, adaptive algorithms, and real-time decision-making. Simulation-based Testing, hardware-in-the-loop Testing, and formal verification are needed to ensure system quality (Fadziso et al., 2022). These methods validate robotic system behavior in many contexts, assuring real-world robustness and dependability. Developing dependable, safe, and high-performing robotic systems requires SQA in the robotic software development lifecycle. SQA methods suited to robotic software will become more critical as robotics advances. Solving difficulties and using sophisticated testing methods may improve robotic system quality and ensure successful deployment in critical applications across industries.

STATEMENT OF THE PROBLEM

Software quality assurance (SQA) approaches customized to the robotic software development lifecycle are needed as robotic systems become more complicated and deployed in various essential applications. Despite robotics and software engineering breakthroughs, SQA approaches for robotic software development still need to be studied (Karanam et al., 2018). Standard SQA methods must handle the complexity of robotic systems, which combine software, hardware, and real-time processing in ways that vary from standard software applications.

SQA integration into robotic software development is complex due to its hybrid and dynamic character. SQA typically targets solitary software components or systems with well-defined inputs and outputs (Kothapalli, 2019). Robotic systems interact with hardware, function in authentic contexts, and adapt to changing situations, requiring SQA methodologies to be rethought. Robotics need real-time performance, hardware-software interfaces, and adaptive solid algorithms for machine learning and autonomous decision-making. Current methods may need to meet these criteria.

This project will identify and assess SQA gaps in robotic software development and offer a framework for integrating robotic system-specific SQA approaches. The research evaluates current SQA techniques in robotics, explores innovative ways to improve software reliability and performance, and develops guidelines or best practices that can be

seamlessly integrated into the robotic software development lifecycle. The project aims to connect conventional SQA techniques with robotic software's changing needs.

This work might progress robotics by assuring excellent quality, safety, and performance in robotic systems. Robots are becoming more common in healthcare, industry, and autonomous cars, making trustworthy and resilient software essential. The robotic software development lifecycle may benefit from SQA integration to increase system dependability, failure risk, and user and operator safety. Moreover, customized SQA approaches may spur innovation in robotic software engineering, laying the groundwork for increasingly sophisticated and competent robots. This work will help robotics software quality assurance become more dependable and successful by filling the research gap. This innovation will improve robotic system performance and safety and encourage industry acceptance and deployment of robotic technology, benefitting society.

METHODOLOGY OF THE STUDY

This secondary data-based analysis examines SQA incorporation into robotic software development. A thorough literature study of SQA and robotic software development academic publications, industry reports, and technical papers is conducted. Relevant, credible, and recent sources guarantee an up-to-date grasp of current procedures and practices. The study identifies gaps and obstacles in applying standard SQA methodologies to robotic systems, evaluates current approaches, and evaluates potential frameworks for incorporating SQA. Data is organized to show trends, methods, and suggestions. This method synthesizes information and insights to improve SQA procedures for robotic software development.

CURRENT SQA PRACTICES IN ROBOTICS DEVELOPMENT

Robotic systems need Software Quality Assurance (SQA) to work consistently and securely in many applications. SQA procedures are used to ensure software quality improves with robotics technology (Kothapalli, 2022). This chapter discusses robotic software development SQA processes, including how conventional methods are modified and when they fail.

Overview of SQA in Robotics

Traditional SQA uses testing and validation methods to ensure software accuracy, performance, and dependability. These methods include unit, Integration, system, and acceptability testing. These methods are modified for robots to meet software-hardware interaction, real-time processing, and dynamic settings.

Unit testing and Verification: Unit testing, a core SQA approach, checks software components and modules for functionality. It also verifies the functioning of robotic software components such as sensor data processing algorithms, control logic, and communication protocols. Robotics requires software-hardware interactions that typical unit testing may only partially cover (Gresse von Wangenheim et al., 2013). Software components are evaluated in a simulated environment to address this in robotic systems. This method helps discover concerns about sensor data interpretation, algorithm performance, and environmental response before the program is implemented on hardware.

Integration Testing and Hardware-in-the-Loop: Integration testing ensures software parts operate together. Software components, including route planning algorithms, sensor

drivers, and control systems, must work together for robotic systems. HIL testing, which uses actual hardware and software simulations to assess software-physical component interaction, is essential in this sector (Kumudha & Venkatesan, 2016). HIL testing lets engineers test robotic systems in a controlled environment to see how software changes affect hardware. This method helps detect concerns about real-time processing, sensor integration, and actuator control. Despite its benefits, HIL testing is resource-intensive and may only cover some operational circumstances, requiring additional Testing.

System Testing and Simulation: The complete robotic system is tested to verify it satisfies specifications and functions as anticipated. In robotic software development, system testing generally uses complex simulation methods to simulate a variety of circumstances that may be difficult to duplicate in physical testing settings. Simulations may evaluate robotic systems' reactions to complex navigation tasks, unanticipated environmental changes, and dynamic human interactions. These simulations help evaluate software algorithm resilience, system performance, and possible difficulties before deployment. Physical Testing is needed to verify simulation findings, which may not precisely reflect real-world situations (Wang et al., 2018).

Continuous Integration and Automated Testing: Robotic software development increasingly uses CI and automated Testing to maintain quality and performance. CI requires constantly merging code changes into a shared repository, and automated Testing finds and fixes bugs early in Development (Kothapalli et al., 2021). Automated testing scripts assess new features, conduct regression tests, and maintain functioning. CI and automated testing speed up robotics development by delivering fast feedback on code changes and decreasing bugs. Robotic software may be tested for functionality, performance, and safety using automated Testing. Automated tests are helpful but must be carefully built to cover a representative collection of cases and updated often.

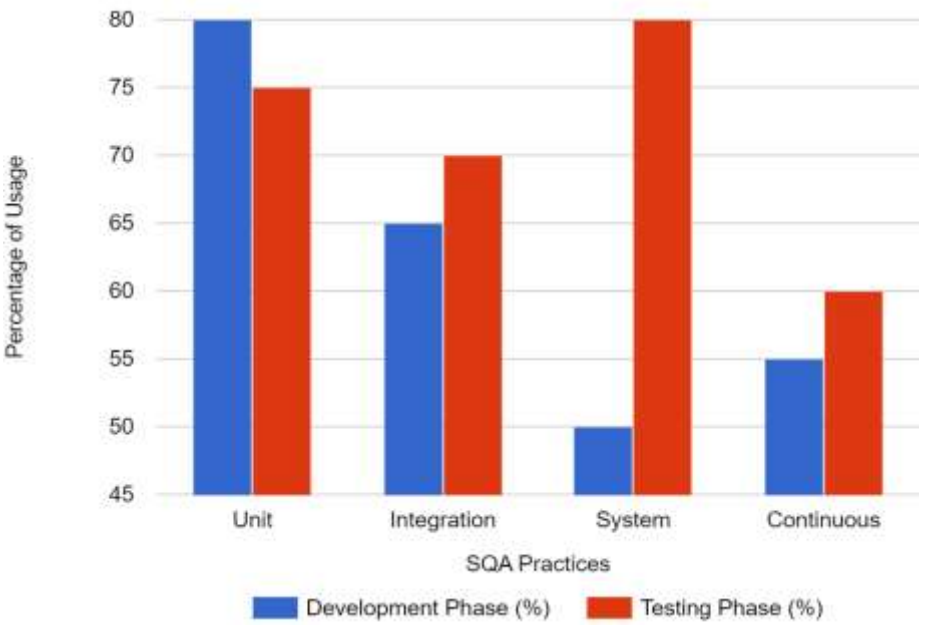

Figure 1: Comparison of SQA Practices in Different Stages of Robotic Software Development

X-Axis includes Unit Testing, Integration Testing, System Testing, and Continuous Integration.

Y-Axis Shows each SQA practice's utilization or effectiveness at distinct development lifecycle phases.

First Bar (Development Phase): Shows each SQA practice's utilization or effectiveness percentage.

Second Bar (Testing Phase): Shows each SQA practice's utilization or effectiveness %.

The Development Phase uses unit testing at 80%, whereas the Testing Phase uses 75%.

Integration Testing is more common in Testing (70%) than Development (65%).

System Testing accounts for 80% of the Testing Phase, concentrating on system-level validation.

Continuous Integration uses all stages equally, with a minor preference for Development (55% vs. 60%).

Current Limitations and Areas for Improvement

While existing SQA procedures are robust for assuring robotic software quality, numerous restrictions remain. Traditional testing methods may miss software-hardware interactions and real-world factors. Robotic systems, especially those with machine learning and autonomous decision-making, are dynamic and adaptable, making standard testing methods difficult (Mohammed et al., 2017a).

Advanced SQA procedures, including real-time Testing, adaptive verification, and complete simulation models, are needed to overcome these restrictions. These techniques should address robotic systems' hardware integration, real-time processing restrictions, and changeable surroundings. Current robotics SQA techniques ensure software quality but must be improved to handle robotic software development difficulties. By adapting these techniques to robotics' difficulties, the industry may increase robotic system dependability, safety, and performance, enabling more sophisticated and capable technologies (Deniz & Cakir, 2018).

CHALLENGES IN SQA FOR ROBOTIC SYSTEMS

Robotic systems' complex and hybrid nature makes integrating Software Quality Assurance (SQA) into the robotic software development lifecycle difficult. Robotic systems use hardware and software, work in dynamic surroundings, and have real-time processing and adaptive behaviors (Mohammed et al., 2018). This chapter discusses the main issues of software quality assurance in robotic systems and how they affect SQA procedures.

Complexity of Hardware-Software Integration

Complex software-hardware Integration is a significant SQA difficulty for robotic systems. Robotic systems use sensors, actuators, and control units with software algorithms to complete tasks. Tight hardware-software connection causes various issues:

- **Testing Hardware Interactions:** Hardware-in-the-loop (HIL) simulations are needed to test software-hardware interactions. Resource-intensive setups may not cover all system combinations and ambient circumstances (Gómez-Sanz & Fuentes-Fernández, 2015).

- **Variability in Hardware Components:** Hardware component variability, such as sensor calibration or actuator performance, may cause software behavior to vary. Due to this diversity, Testing and quality indicators are difficult to establish.
- **Physical Constraints:** Hardware restrictions, such as computational limits or wear and tear, may impact software performance. Advanced Testing and validation are needed to ensure software works reliably under these restrictions.

Real-Time Processing and Determinism

Real-time robotic systems need software to evaluate sensor input and make choices quickly. Real-time requirements provide various SQA challenges:

- **Timing Constraints:** Real-time systems must fulfill severe timing limitations to respond quickly to environmental changes. Real-time performance testing requires assessing the system's capacity to meet deadlines under different situations, which is difficult to replicate and evaluate (Mohan & Shrimali, 2017).
- **Concurrency Issues:** Robotic systems often use concurrent activities like sensor data gathering and control instructions. Implementing testing to ensure these processes interact appropriately and do not generate race situations or deadlocks is tough.
- **Predictability and Stability:** Robotic systems must operate reliably and stay stable under varied situations (Mohammed & Pasam, 2020). Real-time Testing must account for timing difficulties and unexpected inputs that might cause instability.

Adaptability and Machine Learning Integration

Modern robotic systems use machine learning algorithms to adapt and increase performance. SQA faces new hurdles with this Integration:

- **Validation of Adaptive Algorithms:** Training data and environmental interactions may change machine learning models, making validation difficult. Specialized testing methods are needed to ensure these models work consistently and do not behave unexpectedly.
- **Data-Driven Behavior:** The data used to train machine learning algorithms affects their behavior. Testing must account for training data fluctuations and verify system performance in many circumstances, including edge cases.
- **Uncertainty and Robustness:** Machine learning models may impair system performance due to uncertainty. Testing must assess how effectively the system manages uncertain or noisy data and maintains resilience to different inputs (Mohammed, 2021).

Simulation vs. Real-World Testing

Simulations are used to assess robotic systems and software performance. However, simulations have challenges:

- **Accuracy of Simulations**: Effective simulations must properly mimic real-world situations. Simulations and real situations might differ, skewing system performance and reliability estimates.
- **Coverage of Scenarios:** The wide variety of variables a robot may experience makes it difficult to simulate every scenario. Careful simulation design may create testing gaps despite covering a realistic range of cases.
- **Transition to Physical Testing:** Physical Testing must confirm simulation results. This transition may disclose flaws not seen in simulations, requiring repeated changes and Testing.

Safety and Compliance

Robotic systems in sensitive or hazardous situations must be safe and compliant with industry norms. The main obstacles are:

- **Regulatory Standards:** Safety and regulatory regulations are frequently strict in robotics. Software must be documented, tested, and certified to fulfill these criteria, which might take time.
- **Error Handling and Fault Tolerance:** Robotic systems must elegantly handle and tolerate mistakes. Testing for faults and ensuring the system reacts to failures is crucial to safety but challenging.
- **Human-Robot Interaction:** Safety issues for robots interacting with people include ensuring the system operates reliably and safely in human situations. Testing must consider several human interactions and dangers.

The sophisticated combination of hardware, software, and real-time processing makes the robotic system SQA difficult. Advanced Testing, simulation, validation, and safety and compliance are needed to address these difficulties (Mohammed, 2022). These issues must be overcome to ensure robotic system dependability, performance, and safety in varied applications as they progress.

Table 1: Comparison of SQA Practices for Different Robotic Systems

Robotic System Type	Primary SQA Challenges	SQA Practices Used	Effectiveness
Industrial Robots	Hardware-Software Integration, Safety	HIL Testing, Safety-Critical Testing	High effectiveness in Integration and safety.
Service Robots	Real-Time Processing, Machine Learning	Real-Time Performance Testing, ML Validation	Effective for performance and adaptive behavior.
Autonomous Vehicles	Real-Time Processing, Safety, Compliance	HIL Testing, Advanced Simulations, Safety Testing	Comprehensive coverage of performance and safety.

Robotic System Type Classifies robotic systems as Industrial, Service, or Autonomous Vehicles. Each category has various operating needs and problems.

The critical Software Quality Assurance difficulties of each robotic system are listed. Industrial Robots prioritize Hardware-Software Integration and Safety, whereas Service Robots prioritize Real-Time Processing and Machine Learning Adaptability.

SQA Methods Specifies SQA techniques for each robotic system's main difficulties. Examples include HIL Testing, Real-Time Performance Testing, and Machine Learning Validation.

Effectiveness: Assesses how well SQA techniques solve robotic system issues. Hardware-in-the-loop (HIL) Testing helps integrate software with hardware for Industrial Robots and Autonomous Vehicles. At the same time, Real-Time Performance Testing ensures Service Robot responsiveness (Rana et al., 2019).

Table 1 compares how different SQA practices are used in robotic systems and their efficacy in resolving distinct difficulties. It helps stakeholders understand how SQA efforts match the demands of each robotic system type and optimize SQA techniques for system performance and dependability.

PROPOSED FRAMEWORK FOR SQA INTEGRATION

A comprehensive and specialized framework is needed to integrate Software Quality Assurance (SQA) into robotic software development. To improve robotic system dependability, safety, and performance, this framework adapts and extends existing SQA approaches to robotics' particular needs (Nizamuddin et al., 2019). Using different quality assurance levels, the proposed framework tests and validates software and hardware components from Development to deployment.

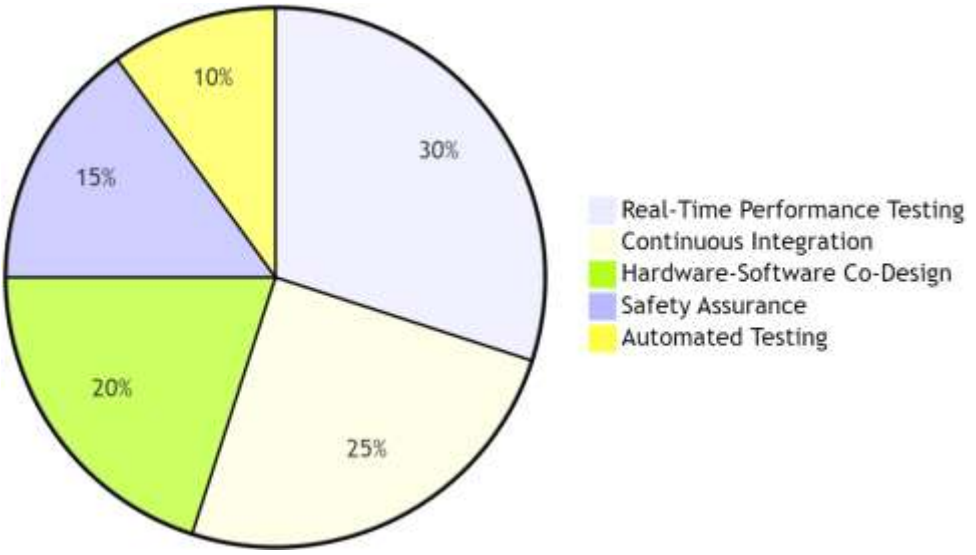

Figure 2: SQA Framework Resource Allocation

The Figure 2 pie chart shows how the robotic system SQA framework components receive resources or effort. It shows which parts receive the most excellent attention and resources. Real-Time Performance Testing receives 30% of resources to ensure system responsiveness and performance under real-time restrictions. Continuous Integration accounts for 25%, emphasizing its relevance in code quality and consistency throughout Development. Hardware-Software Co-Design gets 20% for its crucial role in matching software to hardware restrictions. Safety Assurance receives 15%, demonstrating an emphasis on safety and regulation. Automated Testing supports continuing Testing and validation with the remaining 10%.

The Holistic Testing Approach

Hardware-Software Co-Design: Hardware-software co-design, where hardware and software are designed and tested together, is essential to the framework. This method guarantees that hardware restrictions are considered while developing software. Co-design involves:

- **Early simulation and prototyping:** Modeling hardware-software interactions early in design. This helps identify faults before building prototypes, decreasing development time and cost (Stetter & Simundsson, 2015).
- **Iterative Testing:** Testing and refining hardware and software components. A cohesive system is achieved by continual feedback loops that resolve errors in any area in real-time.

Integrated Testing Environments: Integrating hardware and software simulations to assess system performance realistically. This involves:

- **Hardware-in-the-Loop (HIL) Testing**: Simulating software-hardware interactions in a controlled yet realistic environment. HIL testing detects integration flaws and verifies real-time performance.
- **Simulated Environments:** Using powerful simulation platforms, testing software behavior in diverse environmental settings, including edge situations that may be difficult to duplicate in Physical Testing.

Improved Testing Methodologies

Real-Time Performance Testing: Real-time performance testing is stressed in the framework since robotic systems need it. This includes:

- **Timing Analysis:** This ensures the system fulfills deadlines and completes tasks on time. Real-time capabilities are validated using latency and jitter tools.
- **Concurrency Testing:** Testing for race situations and deadlocks to guarantee smooth and dependable execution of parallel processes.

Machine Learning Validation: The framework provides methods for verifying adaptive behaviors in machine learning-based robotic systems:

- **Data Validation:** Data validation ensures that machine learning models work consistently across situations by testing the system with varied datasets. This entails testing how effectively models handle noisy or missing data and generalize to new data.
- **Behavioral Analysis:** Real-time behavioral analysis of machine learning algorithms to discover and mitigate undesired effects. This involves checking for abnormalities and maintaining system performance.

Continuous Integration and Testing

Continuous Integration: Implementing a comprehensive robotics-specific Continuous Integration (CI) approach, including:

- **Automated Build and Test:** Automate build and Testing to find bugs early and often. This requires functional, performance, and regression automated testing frameworks.
- **Version Control:** Version control systems manage software and hardware configuration changes and ensure all components are integrated and verified.

Automated and Adaptive Testing: Using automated and adaptive Testing to support iterative Development:

Automation Regression Testing involves creating automated regression tests to ensure new changes do not damage current functionality. This sustains software stability and dependability during Development (Ahmed, 2015).

Adaptive Test Scripts: Creating adaptive test scripts that respond to changes in the system's configuration or behavior allows for flexible and efficient Testing as the system develops.

Safety and Compliance

Safety Assurance: Making safety a priority in SQA:

- **Safety-Critical Testing:** Implementing safety-critical testing processes ensures the system fulfills safety requirements and reacts to fault circumstances (Rodriguez et

al., 2019). Test for failure modes and ensure the system can gracefully recover from faults.

- **Compliance Verification:** Regular evaluations and audits verify that industry standards and regulations are met. This requires safety, quality documentation, and certifications (Kazadzis et al., 2018).

People-robot Interaction Testing: Addressing human-robot interaction issues:

- **User Interaction Simulation:** Simulating robot-human interactions to assure system predictability and safety. This involves ergonomic Testing and robot response to human inputs.
- **Behavioral Analysis:** Assessing the robot's response to human interactions to uncover safety hazards and enhance user experience.

The suggested architecture for incorporating SQA into the robotic software development lifecycle addresses robotic system issues comprehensively. The framework ensures robotic systems are dependable, safe, and effective in real-world settings by using comprehensive Testing, upgraded methodology, Continuous Integration, and strict safety and compliance requirements (Ying et al., 2018). This organized method improves robotic software and helps produce more reliable robotic technology.

MAJOR FINDINGS

Integrating Software Quality Assurance (SQA) into the robotic software development lifecycle uncovers various crucial insights and discoveries that illustrate both the difficulties and improvements in guaranteeing robotic system dependability and performance. A complete examination of SQA procedures, difficulties, and the suggested reform framework yielded these conclusions.

The complexity of Hardware-Software Integration: Integrating software and hardware in robotic systems is very complicated. SQA approaches frequently concentrate only on software components, whereas robotic systems need a holistic approach that tackles software-hardware interactions. To overcome this complexity, hardware-software co-design, and HIL testing became essential. These approaches help identify integration problems early and align software and hardware, improving system stability and performance.

Challenges with Real-Time Processing: Real-time processing is essential for robotic systems. Hence, software must be rigorously tested to fulfill timing limitations. Results show that real-time performance testing, including timing analysis and concurrency testing, must ensure robotic systems meet deadlines and manage concurrent tasks. Traditional testing methods fail to capture real-time performance difficulties; therefore, timing limitations and concurrency issues must be addressed.

Machine Learning and Adaptability Issues: Robotic machine-learning algorithms complicate SQA. Our main observation is that adaptive algorithms need specific validation methods. Data validation and behavioral analysis are essential for machine learning models to operate consistently in varied contexts and manage unclear or noisy data. Machine learning algorithms' flexibility demands constant monitoring and testing to avoid undesired behavior and maintain reliability.

Importance of Continuous Integration and Automated Testing: The research emphasizes the importance of Continuous Integration (CI) and automated Testing in software

quality throughout Development. Early and frequent problem detection requires CI approaches like automated build and test procedures. Automated regression testing and adaptive test scripts help manage iterative changes and ensure new features don't break old functionality. These approaches expedite Development and increase software stability and dependability.

Safety and Compliance Considerations: SQA in robots must ensure safety and compliance. Primary results emphasize safety-critical Testing and compliance verification to fulfill industry and regulatory standards. Safety-critical testing techniques ensure robotic systems can manage faults and failures. Robotic systems must comply with appropriate standards and laws to be safe for use in sensitive areas or applications involving humans.

Human-Robot Interaction Challenges: The SQA architecture must handle particular human-robot interaction difficulties. Simulations of human interactions and behavioral analysis are essential for safe and successful robotic system operation in human-interactive contexts. Ergonomic Testing and predictable behavior in response to user inputs improve user experience and reduce safety hazards.

The key conclusions from incorporating SQA into the robotic software development lifecycle underline the necessity for thorough and adaptive quality assurance. Advanced Testing and Continuous Integration are needed due to hardware-software interaction, real-time processing, and machine-learning algorithm problems. Safety, compliance, and human-robot interactions emphasize the need for a robust SQA framework. Addressing these results may lead to more dependable, safe, and high-performing robotic systems, advancing robotics technology and applications.

LIMITATIONS AND POLICY IMPLICATIONS

SQA in robotic software development has various drawbacks. First, Hardware-in-the-Loop (HIL) testing and real-time performance reviews might strain development budgets and timeframes. Test findings may be unreliable because simulations cannot accurately depict complicated real-world settings. Machine learning algorithms' adaptive behaviors make Testing harder since they need ongoing monitoring and validation to maintain performance.

Standards-based robotic system testing techniques and frameworks should be promoted to overcome these constraints. Investing in modern simulation and real-time testing tools should improve SQA accuracy and efficiency. Additionally, regulatory agencies should provide explicit robotics safety and compliance requirements to ensure that software and hardware satisfy high quality and safety standards.

CONCLUSION

Incorporating software quality assurance (SQA) into the robotic software development lifecycle is revolutionary for improving robotic systems' dependability, security, and efficiency. This research emphasizes the intricacies and distinct obstacles encountered in applying conventional SQA approaches to robots, including the complicated interplay between hardware and software, the need for real-time processing, and the Integration of machine learning algorithms. The main conclusions show that considerable modifications to typical SQA procedures are required to meet the unique requirements of robotic systems. Overcoming these obstacles requires Hardware-in-the-Loop (HIL) testing, real-time performance assessments, and specific machine-learning validation methods.

Automated Testing and Continuous Integration (CI) are essential for preserving software quality throughout Development.

Despite these developments, several drawbacks, such as the substantial resource requirements for thorough testing and simulation accuracy, still need to be addressed. Standardized testing procedures, financial investments in cutting-edge simulation technology, and unambiguous legal requirements for compliance and safety are all necessary to lessen these problems.

In conclusion, a comprehensive and flexible strategy is needed to successfully include SQA in the robotic software development lifecycle. Developers may enhance the robustness and reliability of robotic systems, progressing the area of robotics and expanding its applications across diverse sectors by tackling the stated difficulties and using the provided framework. This connection helps create more competent and dependable robots and makes their deployment in real-world situations safer and more efficient.

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